Uncovering and Managing the Impact of Methodological Choices for the Computational Construction of Socio-Technical Networks from Texts

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14. ABSTRACT

This thesis is motivated by the need for scalable and reliable methods and technologies that support the construction of network data based on information from text data. Ultimately, the resulting data can be used for answering substantive questions about socio-technical networks. One main limitation with this approach is that the validation of the resulting network data can be hard to infeasible, e.g. in the cases of covert, past and large-scale networks. This thesis addresses this problem by identifying the impact of coding choices that must be made when extracting network data from text data on the structure of networks and network analysis results. The findings suggest that conducting reference resolution on the text data can alter the identity and weight of 76% of the nodes and 23% of the links, and cause major changes in the value of commonly used network metrics. Also, completely different sets of key nodes are found when reference resolution is applied to the text data prior to conducting relation extraction. Based on the outcome of these experiments, I recommend strategies for avoiding or mitigating the outlined issues in practical applications.

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Abstract

This thesis is motivated by the need for scalable and reliable methods and technologies that support the construction of network data based on information from text data. Ultimately, the resulting data can be used for answering substantive questions about socio-technical networks.

One main limitation with this approach is that the validation of the resulting network data can be hard to infeasible, e.g. in the cases of covert, past and large-scale networks. This thesis addresses this problem by identifying the impact of coding choices that must be made when extracting network data from text data on the structure of networks and network analysis results. The findings suggest that conducting reference resolution on the text data can alter the identity and weight of 76% of the nodes and 23% of the links, and cause major changes in the value of commonly used network metrics. Also, completely different sets of key nodes are found when reference resolution is applied to the text data prior to conducting relation extraction. Based on the outcome of these experiments, I recommend strategies for avoiding or mitigating the outlined issues in practical applications.

When extracting socio-technical networks from texts, the set of relevant node classes might go beyond the classes that are typically supported by tools for named entity extraction. I address this lack of technology by developing an entity extractor that combines a model of socio-technical networks that originates from the social sciences, is theoretically grounded, and has been empirically validated, with supervised machine learning techniques that are based on probabilistic graphical models. This thesis does not stop at showing that the resulting prediction models achieve state of the art accuracy rates, but I also describe the process of integrating these models into an existing and publically available end-user product such that these models can be readily used by others on new data.

While a plethora of methods exists for building network data from information explicitly or implicitly contained in text data, there is a lack of research on how the resulting networks compare with respect to their structure and properties. This also applies to the networks that can be extracted by using the aforementioned entity extractor as part of the relation extraction process. I address this knowledge gap by comparing the networks extracted with this process to network data built with three alternative methods: text coding based on thesauri that associate text terms with node classes, the construction of network data from meta-data on texts, such as key words and index terms, and building network data in collaboration with subject matter experts. The outcome of this suggests that thesauri generated with the entity extractor developed herein need adjustments with respect to particular categories and types of errors. I am providing tools and strategies to assist with these changes. The results show that once these changes are

made and in contrast to manually constructed thesauri, the prediction models generalize with acceptable accuracy to other domains (from news wire data to scientific writing and emails) and writing styles (from formal to casual). The comparisons of networks constructed with different methods show that ground truth data built by subject matter experts are hardly resembled by any automated method that analyzes text bodies, and even less so by exploiting existing meta-data from text corpora. Thus, aiming to reconstruct social networks from text data leads to largely incomplete networks. My conclusions outline which type of information about socio-technical networks is best captured by what network data construction method, and how to best combine these methods in order to retrieve reliable network data.

When both, text data and relational data, are available as a source of information on a network, people have previously integrated these data by enhancing social networks with content nodes that represent salient terms from the text data. I present a methodological advancement to this technique, and test its performance on different datasets. By using this approach, multiple types of behavioral data, namely interactions between people as well as language use, can be taken into account. I conclude that extracting content nodes from groups of structurally equivalent agents can be an appropriate strategy for enabling the comparison of the content that people produce, perceive or disseminate. These equivalence classes can represent a variety of social roles and social positions that network members occupy. At the same time, extracting content nodes from groups of structurally coherent agents can be suitable for enabling the enhancement of social networks with content nodes. The results from applying the latter approach include a comparison of the outcome of topic modeling; an efficient and unsupervised information extraction technique, to the outcome of alternative methods, including supervised entity extraction. The findings suggest that key entities from meta-data knowledge networks might serve as proper labels for unlabeled topics, and that unsupervised and supervised learning retrieve similar entities as highly likely members of highly likely topics and key nodes from text-based knowledge networks, respectively.

In summary, the contributions made with this thesis help people to collect, manage and analyze rich network data, which is a precondition for asking substantive questions and testing hypotheses and advancing theories about networks. This thesis uses an interdisciplinary and computationally rigorous approach to work towards this goal; thereby advancing the intersection of network analysis, natural language processing, and computing.

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1 Introduction and Overview

1.1 Thesis Statement

This thesis is motivated by the need for scalable and reliable methods and technologies that support the collecting of network data from natural language text data, and the usage of the extracted data for answering substantive questions about socio-technical networks. The methodological findings and the technology provided with this thesis improve the applicability of language technologies for generating socio-technical network data based on text data; hereby advancing the intersection of network analysis and text analysis. This thesis contributes to the actionable meaning of network data by providing methods that leverage theories from the social sciences to construct and analyze network data, and to combine text data and network data for analysis.

1.2 Network Analysis

Socio-technical networks represent interactions between people, groups and infrastructures (K.M. Carley, 2002a). These networks are ubiquitous and impact society on many dimensions (M. Newman, 2010). Realizing the relevance of networks, people from public administrations, business corporations, funding agencies, and communities of practice, among others, have been asking questions such as:

- How can we efficiently collect, manage and analyze data about socio-technical networks such that we are able to capture and understand the relevant properties and behavior of networks?
- What are the underlying forces that drive the evolution and dynamics of networks?
- What are the implications of certain network characteristics for practical purposes, such as building and managing teams and organizations, designing and adapting policies, disseminating information, and fostering innovation?
- How reliable are these network data and respective findings?

In the field of network analysis, people have developed methods, metrics and theories that help to address these questions (Brandes & Erlebach, 2005; Freeman, 2004; Leinhardt, 1977). More specifically, *Social Network Analysis* (SNA) is defined as the "testing of theories about structured social relationships" (Wasserman & Faust, 1994, p. 17). Originally, SNA has been advanced by social scientists who used it for gaining a rich and thorough understanding of small groups in a retrospective fashion (J. Mitchell, 1969; Newcomb, 1961; B. Ryan & Gross, 1943; Sampson, 1968). Therefore, the original network analytical measures were defined for

connections between social agents, i.e. people and groups (Bonacich, 1987; Freeman, 1979; Wasserman & Faust, 1994).

The scope of network analysis as a research method as well as of social networks as an object of study has been broadened and adopted across disciplines. Consequently, a large body of new models, theories, methodological advances and applications has been developed (see for example Carrington, Scott, & Wasserman, 2005).

Network analysis is sometimes also referred to as *Network Science*, which is an extension of SNA. Network science is defined as "the study of network representations of physical, biological, and social phenomena leading to predictive models of these phenomena" (National_Research_Council, 2005, p. 28). In network science, synthetic as well as empirical data are often used to study the quantitative properties, structure and dynamics of relational data (see for example Barabási & Albert, 1999; Erdős & Rényi, 1959; Simon, 1955; D.J. Watts & Strogatz, 1998). Network scientists have developed a wide range of efficient and scalable computational solutions for collecting, managing, and analyzing relational data (see for example MEJ Newman, Barabasi, & Watts, 2006). I herein refer to both, SNA and Network Science, which are different labels for the same field, namely the study of relational or network data, as *network analysis*.

Based on the concept of *socio-technical systems* (Emery & Trist, 1960), the web of interactions within complex societal systems and their infrastructures is referred to as *socio-technical networks*. Most socio-technical networks exhibit characteristics of *complex systems*: they are in flux, vary in size, and feature a multitude of interactions and interdependencies between variables that can lead to radical changes in the system's behavior (Kauffman, 1995). The concept of socio-technical networks includes virtual and online networks.

In summary, network analysis has been adopted by researchers and practitioners as a general utility method – much like statistics – in a variety of fields, including business and economics (R. S. Burt & Janicik, 1996; Saaty, 2005), public policy (D. Krackhardt, 1990), social science and anthropology (K.M. Carley, 2002a; Johnson, Boster, & Palinkas, 2003), and computing (Balasubramanyan, Lin, & Cohen, 2010; J Leskovec, Kleinberg, & Faloutsos, 2007). Furthermore, networks, especially social networks, have become a popular object of study (MEJ Newman, et al., 2006).

1.2.1 Network Metrics

Core network metrics were developed with respect to social networks, i.e. people to people connections. In general, network metrics are defined on the node level, graph level, or aggregates of nodes. The core metrics include:

- *Node level*: Centrality, which measures the prominence of an actor with respect to the number of direct connections she has (degree centrality), her distance to other nodes in the network (closeness centrality), how often she is positioned on the shortest path between any pair of nodes (betweenness centrality), and how close she is to other prominent players (eigenvector centrality) (Bonacich, 1987; Freeman, 1979).
- *Graph level*: The abovementioned centrality metrics are also defined on the graph level, where they are based on the respective centrality score nodes in the network, among other properties (Wasserman & Faust, 1994).
- *Graph level*: Density, which measures the ratio of realized links to possible links (Wasserman & Faust, 1994).
- *Other aggregates*: The number of triangles, simmelian ties (edges in triangles), and cliques (maximally connected subgraphs) that an agent is involved in, or that are present in a network (D. Krackhardt, 1998; Wasserman & Faust, 1994).

A more complete definition of these metrics and all other metrics used in this thesis is provided in Table 153. While the abovementioned metrics can be used for networks that involve any node class, network metrics have also been developed and defined for specific node classes (K.M. Carley, 2002b; D. Krackhardt & Carley, 1998). For example, the “ knowledge load” metric measures the average number of nodes from the knowledge class that an agent is linked to (K.M. Carley, 2002b).

1.3 Network Data

Data on socio-technical networks can be collected through a variety of methods; most of which can be categorized as surveys (DM Krackhardt, 1987; B. Ryan & Gross, 1943), questionnaires (Newcomb, 1961), (participating) observations (J. Mitchell, 1969; Sampson, 1968), experiments (Milgram, 1967), and simulations (K.M. Carley, 1991). These methods can be conducted in a manual or computer-assisted fashion (H. R. Bernard, et al., 1990).

Traditionally, researchers have used methods that required first-hand experience or direct interactions with network participants, such as (computer-assisted) personal and telephone interviews (Newcomb, 1961) and pile sorting (Boster, Johnson, & Weller, 1987). Though cumbersome and expensive in term of time and costs for trained personnel, these methods have

been widely used across various disciplines, including sociology (H. R. Bernard, et al., 1990), anthropology (H. R. Bernard, et al., 1990; Johnson, et al., 2003; J. Mitchell, 1969), linguistics (J. Milroy & Milroy, 1985), political science (Hämmerli, Gattiker, & Weyermann, 2006), public policy and organization science (D. Krackhardt, 1990), and business (Galaskiewicz & Burt, 1991).

Over the last decade, network data collection methods have been adopted for online settings. Lately, harvesting the (participatory) web has become a widely used strategy for gathering network data (Parastatidis, Viegas, & Hey, 2009). Popular data sources include websites (P Gloor, et al., 2009), social networking sites such as Facebook and Twitter (Lampe, Ellison, & Steinfield, 2007), and other platforms for social interaction, such as blogs (Adar & Adamic, 2005), chats (Paolillo, 1999), and virtual worlds including online games (Bainbridge, 2007; Keegan, Ahmed, Williams, Srivastava, & Contractor, 2010).

1.3.1 Text Data as a Source for Network Data

The functioning and evolution of socio-technical networks involves the frequent production, processing and flow of information. This information often occurs in the form of natural language text data, and can originate from within or outside of the socio-technical network of interest. It has long been recognized that such text data can serve as a single or complementary source of information about networks (R. Burt & Lin, 1977; K.M. Carley & Palmquist, 1991; Glaser & Strauss, 1967). The availability of this type of data has stimulated a long tradition in linking text analysis and network analysis. Most of the prior research on bringing together text analysis and network analysis falls into one or more of the following categories:

- Analyzing semantic networks (for a review see Van Atteveldt, 2008).
- Defining network metrics for assessing relational data distilled from texts (K.M. Carley, 1997b).
- Developing methods, data structures and technologies for extracting relational data from texts (for reviews see J. Diesner & K. Carley, 2010; Mihalcea & Radev, 2011).

Examples for types of the text data that have been used for network analysis include news wire data (K. M. Carley, Diesner, Reminga, & Tsvetovat, 2007; Van Atteveldt, 2008), legal documents (Baker & Faulkner, 1993; Feldman & Seibel, 2006), interview transcripts (K.M. Carley, 1988; Sageman, 2004), interpersonal communication such as traditional and electronic mail (Diesner, Frantz, & Carley, 2005; Fitzmaurice, 2000), and archival and historic data (R. Burt & Lin, 1977). More recently, text data that were generated as byproducts of (computer-supported) collaboration processes have become a popular source for collecting network data. Examples include descriptions of work processes (Corman, Kuhn, McPhee, & Dooley, 2002; J.

Danowski & Edison-Swift, 1985), job training scenarios (Weil, et al., 2008), e-learning environments (Haythornthwaite, 2001), team meetings (Dabbish, Towne, Diesner, & Herbsleb, 2011), software development initiatives (Cataldo & Herbsleb, 2008), wikis (Chang, Boyd-Graber, & Blei, 2009), and virtual worlds such as online games (Landwehr, Diesner, & Carley, 2009).

In general, people have been extracting three types of information from text data: First, one-mode networks, in which all nodes are of the same type. The resulting networks are often called concept networks (for a review see J. Diesner & K. Carley, 2010). Concepts are considered as abstract representations of the information that people conceive in their minds (J. F. Sowa, 1984). Sometimes, concept networks are also called semantic networks, even though semantic networks are defined more strictly (Allen & Frisch, 1982; J. Sowa, 1992; Woods, 1975). Concept networks have been used to answer questions like: What are the key concepts in corpus? What ideas and topics emerge, spread and vanish in socio-technical systems? How do such diffusion processes happen over time? (Corman, et al., 2002; Doerfel & Barnett, 1999; P Gloor, et al., 2009; Griffiths, Steyvers, & Tenenbaum, 2007; J. Leskovec, Backstrom, & Kleinberg, 2009)

Second, the nodes in concept networks can be further categorized into specific node classes, such as agents, locations and resources (Barthelemy, Chow, & Eliassi-Rad, 2005; Diesner & Carley, accepted). Such multi-mode networks are also referred to as meta-networks (K.M. Carley, 2002a). Multi-mode network have been used to answer questions like: Who is talking to whom about what? Who are the key players in an organization? How does an agents' prominence differ depending on their access to resources and knowledge? (K. M. Carley, et al., 2007; Hämmerli, et al., 2006; Van Atteveldt, 2008)

Third, texts can also be considered as a node class themselves. These nodes can be linked to the social agents who have authored or cited a text, or are referenced in a text (Hummon & Doreian, 1989; C. Roth, 2006). Attributes of the text data, e.g. meta-data such as index terms, can serve as additional nodes or node attributes (Pfeffer & Carley, under review). Networks in which text are considered as nodes can used to ask questions like: Who has what impact on the advance of an idea or a discipline? How does co-publishing within versus across organizations relate to the acquisition of research funding? (Small, 1973; Wagner & Leydesdorff, 2005)

Overall, network analysis has been used on unstructured, semi-structured and structured text data. Unstructured means that only plain text bodies are available. Semi-structured means that chunks or tokens in the data are annotated with additional information, such as turns between speakers. Structured means that the text bodies are annotated such that they allow for filling

templates that have a predefined structure, such as tables and databases, or that the annotations adhere to a predefined taxonomy or ontology.

1.4 Opportunities and Challenges of Bringing Together Text Analysis and Network Analysis

Historically, hand coding has been a dominant way in which networks have been extracted from texts (H. Bernard & Ryan, 1998; Glaser & Strauss, 1967; Novak & Cañas, 2008). Due to technical advances, the storage and retrieval of text data with information about networks has become fast, cheap, and easy (Shapiro, 1971; Trigg & Weiser, 1986). Modern information and communication technologies, such as the internet, cell phones, and social networking services, have further expedited and facilitated the production, distribution and collection of network data as well as text data pertaining to networks (Eagle & Pentland, 2006; Parastatidis, et al., 2009). Since hand coding does not scale up the amount of text data available for analysis, there is a broad need among researchers and practitioners for theories, methods, metrics, and tools that support efficient knowledge discovery and reasoning about network data extracted from text data (K.M. Carley, 2002a; P. Schrodt, 2001; Shen, Ma, & Eliassi-Rad, 2006). At a minimum or as a starting point for further analysis, end users are interested in text mining solutions that help them to gain a first pass understanding of the properties and dynamics of socio-technical networks (Bond, Bond, Oh, Jenkins, & Taylor, 2003; A. McCallum, 2005; Parastatidis, et al., 2009). In addition to this purpose, people have been using data about networks extracted from texts for the following purposes:

- Populating relational databases, which can be used for information search and retrieval purposes (Brin, 1999; Cafarella, Banko, & Etzioni, 2006; Fellbaum, 1998; Gerner, Schrodt, Francisco, & Weddle, 1994; King & Lowe, 2003).
- Input for further computations, such as simulations of socio-technical systems and machine learning procedures (K. M. Carley, et al., 2007; Pearl, 1988).
- Generating network visualizations, which can be used e.g. to engage people in communication about complex systems and conflicts (Hämmerli, et al., 2006; Hartley & Barnden, 1997; Shen, et al., 2006).
- Iterative testing and development of theories about socio-technical systems (Glaser & Strauss, 1967; J. Milroy & Milroy, 1985).
- Monitoring and improving organizational and collaborative processes (Corman, et al., 2002; Dabbish, et al., 2011; Weil, et al., 2008).

- Assessment of conflict escalations and early warning systems for crises, as well as a data source for analyzing crises (Bond, et al., 2003; Hämmerli, et al., 2006; Zagorecki, Ko, & Comfort).

Even though the combination of text analysis and network analysis has led to advances in research and practical applications in either field, it also involves unique challenges. Some of these challenges are addressed in this thesis:

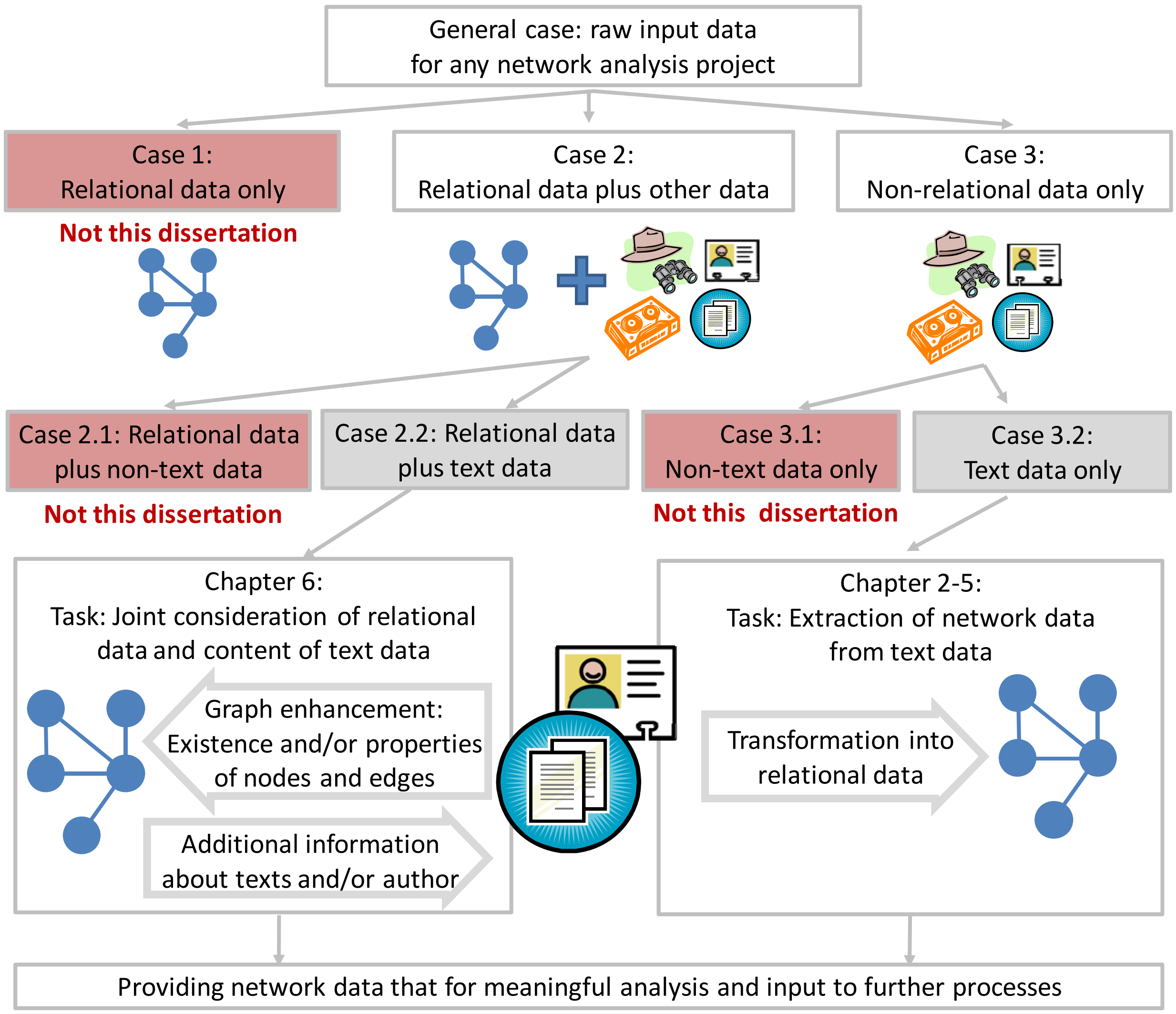
- The efficient and reliable extraction of nodes and links from text data (Corman, et al., 2002; A. McCallum, 2005). This issue mainly applies to unstructured text data.
- The lack of sufficient amounts of (reliable) ground truth that can be used for validating network data extracted from texts. This challenge applies to unstructured, semi-structured, and structured text data.
- The fusion of unstructured and structured information from texts about networks.

Besides these challenges, there are many others, which are beyond the scope of this thesis. Examples include biases in texts, emotions and sentiments expressed by members of social networks in text data (Shanahan, Qu, & Wiebe, 2006), and adapting existing methods and tools to new domains and genres (Gupta & Sarawagi, 2009), such as social media data and email data (A McCallum, Wang, & Mohanty, 2007).

1.5 Organization of Thesis

The chapters in this thesis are organized by the types of availability of text data for network analysis and the structuring of these text data; going from the availability of unstructured text data only (chapters 2 - 4) to (semi-)structured text data plus other sources for network data (chapters 5, 6). These different options are depicted in Figure 1 and described below. Table 2 summarizes which type of text structure is addressed in which chapter, and which types of structure the respective findings apply to.

Figure 1: Organization of thesis*



* Gray fields mark the situations that are addressed herein, and red fields mark the situations that are not considered.

Availability of text data only (Figure 1, case 3.2): The structure and behavior of networks can be explicitly or implicitly encoded in the text data. Sometimes, such texts are the only source of information available about a network. Most of these cases fall into one or more of the following categories, which are not exclusive:

- Networks that are inaccessible or unobservable for researchers:
  - Covert networks, e.g. illegal business coalitions (Baker & Faulkner, 1993) and adversarial groups (Krebs, 2002; Sageman, 2004).
  - Networks that do not exist anymore, e.g. former regimes (Seibel & Raab, 2003) and bankrupt companies (Diesner, et al., 2005).

- Virtual networks that are not based on an underlying real-world network, or that are nothing more than the data traces produced in these networks, such as blogs (Adar & Adamic, 2005). We refer to such networks as WYSIWII (What-You-See-Is-What-It-Is) (J. Diesner & K.M. Carley, 2009).
- Very large networks, where conducting surveys within appropriate network boundaries would be prohibitively expensive (R. Burt & Lin, 1977), e.g. geopolitical networks.
- Groups that do not produce large amounts of readily available interaction data, e.g. ethnic groups (J. Mitchell, 1969), or interactions in regular offline, non computer-supported settings.
- Semantic networks that represent mental models, i.e. structured representations of information that people conceive in their minds (Klimoski & Mohammed, 1994; Rouse & Morris, 1986).

In these cases, network data can be extracted from text data. From an NLP point of view, this is an Information Extraction (IE) task referred to as Relation Extraction (REX) (A. McCallum, 2005). REX is particularly valuable when text data are the only source of information about a network. However, the network data resulting from REX are hard to verify when (reliable) ground truth data are missing (Klerks, 2001). This is often the case for covert and large-scale networks, for example. This limitation is even more severe if we consider the fact that the computational and interdependent steps needed for highly accurate REX solutions impact the structure and properties of the distilled network data. These impacts are insufficiently understood (Corman, et al., 2002). I start to bridge this knowledge gap in chapter 2, where I investigate the amount and bounds of variation in network structure that is due to engineering decisions made when building relation extraction tools and end-users decisions made when applying these tools.

In the social sciences, people have developed theoretically grounded and empirically tested models of socio-technical networks. These models can be used as ontologies for defining the entity classes that are relevant for REX (Barthelemy, et al., 2005; Van Atteveldt, 2008). One of these models is the meta-matrix model, which contains entity classes including and beyond the set of classes typically considered for REX (K.M. Carley, 2002a; D. Krackhardt & Carley, 1998). However, there is a lack of:

1. Technologies that facilitate the efficient extraction of network data that adhere to the meta-matrix model.
2. Evaluations of the performance of such extraction technologies in practical applications settings beyond experimental studies that serve the formal model validation based on ground truth data.

The first need is addressed in chapter 3, where I develop and evaluate prediction models for entity extraction. These models distill instances of meta-matrix entity classes from unstructured text data. The retrieved entities can be used as nodes for constructing socio-technical networks. In chapter 4, I describe how the developed entity prediction models are integrated into an end-user software product, and the operational implications of this process.

The second need is addressed in chapter 5, where I evaluate the performance of the prediction models in different, practical application contexts. In that chapter, I also compare the resulting networks with respect to their structure and properties to networks generated with alternative methods from the same data. The ultimately goal with this work is to provide network data that can be used to answer substantive questions about socio-technical networks. The comprehensive analyses needed to answer such questions require additional empirical studies, which are beyond the scope of the thesis. The point with this chapter is rather is to illustrate the process of going from research questions to the collection and analysis of network data. I describe the methodological steps and choices involved in this process such that they can serve others as a guideline for conducting empirical studies.

Joint availability of text data and network data (Figure 1, case 2.2): Sometimes, in addition to text data, further sources of information about a network are available, such as relational data, or meta-data from which relational data can be constructed. Prominent examples for this situation include:

- Surveys that ask respondents not only for information about entities and relations (relational data) (see for example DM Krackhardt, 1987), but also for answers to questions that further describe the nature of nodes and links (text data) (Palmquist, Carley, & Dale, 1997).
- Communication networks (who is talking to whom, relational data) about what (text data) (Monge & Contractor, 2003).
- Co-citation networks, where person *A* is linked to person *B* if *A* cited *B* (relational data) in a paper (text data) (Hummon & Doreian, 1989; C. Roth & Cointet, 2010).
- Web science studies that combine data on the connectivity between URIs (relational data) with the content of the corresponding webpages (text data) (Adar & Adamic, 2005; Kleinberg, 2003).

Two approaches are commonly used for representing and analyzing both types of data: First, the text data and the relational data are analyzed separately from each other. Second, the text data are reduced to the fact, frequency or likelihood of the flow of information between nodes. This is typically done by representing the exchange of information as a link. While the second approach

is efficient and acknowledges that information exchange has taken place, it does not consider the substance of text data. However, we know that without considering the content of text data, or by analyzing text data and other data about a network in a disjoint fashion, we are limited in our ability to understand the effects of language use in networks. This includes the transformative role that language can play in networks, and the interplay and co-evolution of information and the structure and behavior of networks (Corman, et al., 2002; J. A. Danowski, 1993). Approaches to considering the content of texts build on the idea that "travelling through the network are fleets of social objects" (J. A. Danowski, 1993, p. 198), where these objects can be language, norms, practices, and other types of behavior and interactions (Bourdieu, 1991; Eckert, 1998). The lack of integration and joint analysis of text data and other types of data about networks is addressed in two places: First, in chapter 5, where I show how the networks extracted from texts and networks built from meta-data agree in structure and key entities. Second, in chapter 6, where I propose and demonstrate a methodology for jointly considering relational data and text data.

Finally, text data sources may also contain non-textual information that are not addressed herein, such as images, audio and video data (Figure 1, Case 2.1). These additional types of data might contain further information about networks. While I do not consider these alternative types of non-relational data herein, the methods for and insights about comparing and integrating text networks and networks from other sources might serve others as a starting point for bringing together different types of information about networks.

1.5.1 Datasets Used in Thesis

For the experimental work in chapters 2 and 3, I used external, validated, ground truth corpora. With this kind of data, I am able to measure the actual and precise impact of coding choices on network data, and to validate the prediction models in a reliable and controlled fashion. These datasets are introduced in chapter 2.

For the applied work in chapters 5 and 6, I use a corpus that we have previously collected (Enron), and two corpora that I have collected and prepared for this thesis (Sudan, Funding). The Enron data contain emails from employees in the Enron corporation (Diesner, et al., 2005). The Sudan corpus consists of news wire articles about the Sudan, plus meta-data on these articles, such as their release date and index terms. The Funding corpus comprises proposals of funded research projects, plus information about the people involved in these projects, and additional details about the projects, such as amount of funding awarded. These datasets are introduced in detail in chapter 5. Table 1 compares these datasets along various characteristics. Even though

these datasets are from different domains - namely industry, politics, and science - they share a few characteristic:

- All datasets contain natural language text data.
- All datasets contain some meta-data.
- All datasets contain time-stamped, long-term, over-time data.

Much of the recent work on combining text analysis and network analysis investigates the properties and benefits of interaction between humans via social media and computer supported collaborative work environments. In contrast to that, the datasets used herein represent networks that involve conflicts (Enron, Sudan) and competition (Funding). Prior research suggests that for such networks, the formation and cohesion of groups might be driven by external pressures, such as scarce resources and struggle for power, more so than by group-internal characteristics, such as shared identity and the desire to collaborate. These properties have shown to foster the development of strategic alliances (Fitzmaurice, 2000). For situations in which groups need to balance concealment and coordination, prior research has provided empirical evidence for how these networks differ from overt networks (Baker & Faulkner, 1993). However, this thesis is focused on methodological questions instead of substantive questions about the considered datasets and networks. Nonetheless, the technologies and methods developed and evaluated herein are tested on these datasets, such that the gained insights can be expected to generalize within the stated boundaries to other datasets from similar domains. This helps to complement knowledge about classic cooperation and collaboration networks, and addresses shortcomings with methodological issues for analyzing covert networks (Klerks, 2001; Skillicorn, 2008).

Table 1: Comparison of datasets

Dimension	**Sudan Corpus**	**Funding Corpus**	**Enron Corpus**
Domain	Geo-political : Politics, conflict, covert activities	Science: Innovation, collaboration, competition	Business: Innovation, politics, covert activities
Social network	Implicit in text bodies	Explicit in project descriptions	Explicit in emails headers
Semantic information/ network	Implicit in texts	Implicit in abstracts	Implicit in email bodies
Size	79,388 articles	55,972 proposals	52,866 emails
Time span	12 years	25 years	6 years
Original access to data	Public	Beginning: internal If funded: public	Internal
Intended audience	The public	Program managers	Addressees

	Analysts	Scientific community	
Style	Formal: journalistic	Formal: scientific	Formal and informal

Table 2: Types of text data and networks used in thesis*

<table>
<tr><th rowspan="2">Chapter</th><th colspan="2">Experiments and Analyses</th><th colspan="2">Insights gained and technology built applicable to</th></tr>
<tr><td>Network modality</td><td>Type of structure of text data</td><td>Network modality</td><td>Type of structure of text data</td></tr>
<tr><td>2: Investigation of impact of coding choices on network structure and network analysis results.</td><td>One-mode networks (reference resolution project, windowing project).
Multi-mode networks (windowing project).</td><td rowspan="2">Unstructured</td><td rowspan="4">One-mode networks and multi-mode networks.</td><td rowspan="3">Mainly unstructured data. Also applicable to structured data.</td></tr>
<tr><td>3. Entity Extraction for providing nodes for constructing socio-technical networks.</td><td rowspan="2">One-mode networks and multi-mode networks.</td></tr>
<tr><td>5. Comparison of networks generated with various relation extraction techniques.</td><td rowspan="2">Unstructured:
Sudan: news articles
Funding: research proposal
Enron: email bodies
Structured:
Sudan: meta-data
Funding: meta-data
Enron: email headers</td></tr>
<tr><td>6. Method for combining content of text data with social network data.</td><td>One-mode networks of different modes (concept network, social network).</td><td>Unstructured data for which meta-data are also available.</td></tr>
</table>

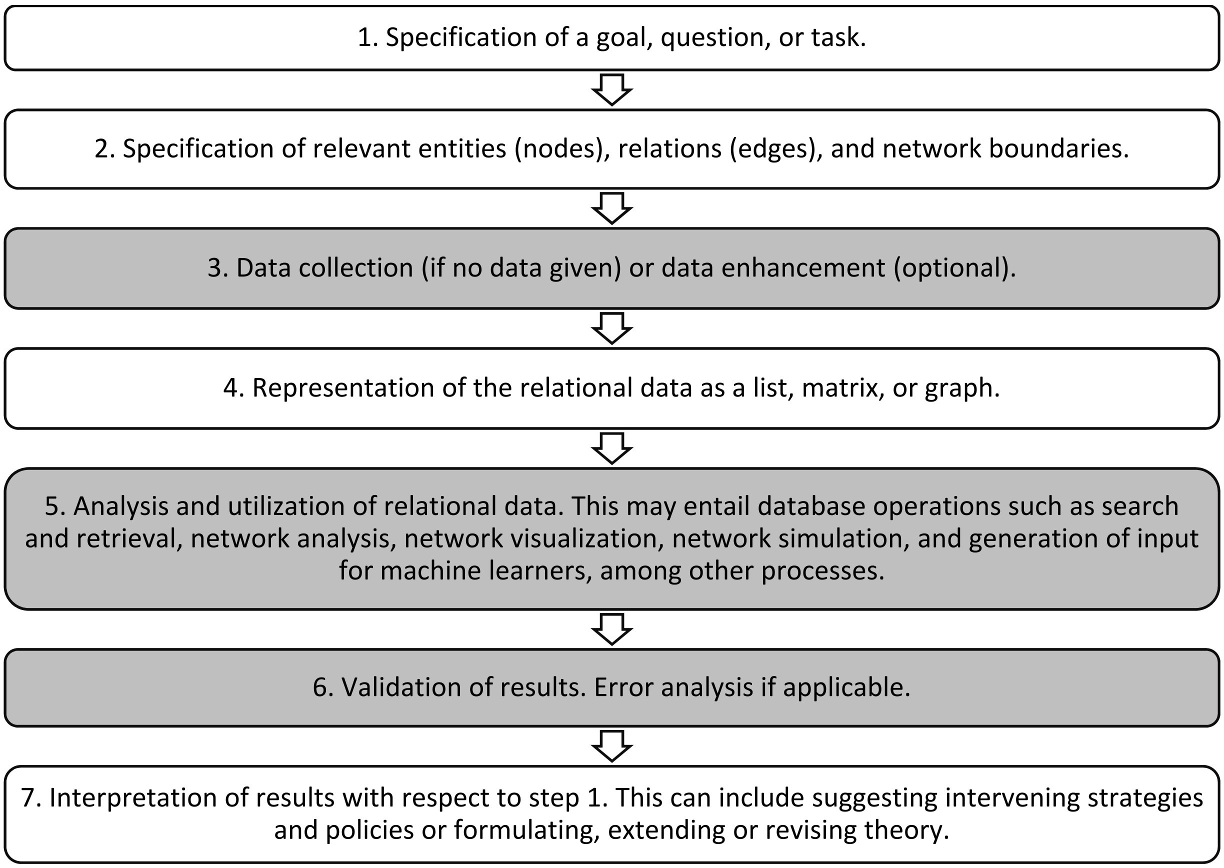
* Using the definition of structured and unstructured data presented in this chapter, most data annotated for information extraction purposes falls under the category of structured data. However, the actual texts in such data sets are unstructured. Entries marked with a * in this table represented cases in which unstructured text data with annotations that bring some form of structure to the text are used.

1.6 The Network Analysis Process

The questions addressed in this thesis relate to certain steps in the overall network analysis process. Since network analysis has originated from various fields with cross-disciplinary influences, the methodology for conducting network analysis is less standardized than research methodologies that are more specific to a field. Synthesizing prior descriptions of the network analysis process (Knoke & Yang, 2008; Wasserman & Faust, 1994) suggests that this process comprises seven steps as shown in Figure 2. In this figure, the steps towards which this thesis

makes a contribution are marked as gray fields. Since these individual steps are highly interdependent, any individual step can be assumed to have recuperations on other steps as well as the overall outcome of a network analysis project.

Figure 2: Network analysis process and steps focused on in this thesis (gray)



1.7 From Text Data to Network Data to Knowledge

The focus of this thesis is on the collection, analysis and validation of network data extracted from texts. I distinguish between network data and relational data. What is the difference, and why does it matter?

Relational data, also referred to as *graphs*, consist of vertices, also called nodes, and of edges, also called arcs, links, or connections. The edges connect the nodes. Additionally, nodes and edges can have weights, attributes, types, and probabilities, and links can furthermore have directions. Nodes can represent instances of one (one-mode) or more (multi-mode) types of entity classes, such as “agent” and “information”. Edges can represent instances of one (uni-plex) or more (multi-plex) types of relationships, such as “collaboration” or “trade” (K.M.

Carley, 2002a; Wasserman & Faust, 1994, p. 79). *Social networks*, for example, involve only entity of the type "agent".

Network data consists of relational data plus additional data that help to contextualize and interpret relational data (Alderson, 2008). Thus, relational data are an indispensable subset of network data, but are insufficient for revealing comprehensive stories about socio-technical networks (Corman, et al., 2002).

It has been previously argued that in order to allow for meaningful analysis of socio-technical networks and for answering substantive questions about such networks, linked data need to be transformed into information, and information into knowledge (Parastatidis, et al., 2009). Translating this argument into network terms means to go from relational data to network data, and from network data to knowledge. Transforming relational data into network data requires the enhancement of relational data with additional data (Alderson, 2008). This is typically achieved by bringing together various types or sources of information about a network. This theoretical argument has been put into action by applying one or more of the following strategies:

- Including attributes that describe relevant characteristics of nodes and/or edges (Sampson, 1968).
- Considering different views of a network (DM Krackhardt, 1987).
- Enhancing relational data with additional data that help to fix the context of the relational data.

Additional data about networks are often referred to as meta-data. Widely adopted types of meta-data are temporal and spatial information, such as timestamps of events or the geophysical position of nodes (Eagle & Pentland, 2006; Snijders, 2001). Another type of additional data are natural language text data (K.M. Carley & Palmquist, 1991; J. A. Danowski, 1993). This thesis is confined to the latter option, i.e. using text data to construct and enrich relational data and network data. While texts generated by humans can be considered as a type of behavioral data, meta-data can be generated by humans or automatically, e.g. in the case of key words for documents. This thesis is focused on methods for utilizing human-generated text data pertaining to socio-technical networks, including meta-data.

Going from networks to knowledge means to perform analyses such that substantial questions about networks can be answered. In general, this requires the usage of methods and computation of metrics that are appropriate for the given network data. Sometimes, using generic matrix operations or calculating metrics that are defined independently of the type of nodes or edges is most appropriate and sufficient. This often applies to research problems in network science. In other cases, methods and metrics are needed that take the types or other characteristics of nodes

and edges into account (K.M. Carley, 2002a; D. Krackhardt & Carley, 1998). This can apply to the analysis of multi-mode or multi-plex networks, for instance (Cataldo, Herbsleb, & Carley, 2008; D. Krackhardt & Carley, 1998). When this approach is more appropriate, there are several models and measures available that are based on theories about the system that the network data represent. I follow this route by using a theoretically grounded model of socio-technical networks to inform the selection of entity types to extract from text data.

In summary, going from relational data to network data to knowledge helps to make the substance or meaning of network data actionable. Here, actionable means extractable, explicitly representable, and useful for answering substantive questions about socio-technical networks. Sometimes, this process is even used to develop strategies for taking further action, such as suggesting policies or designing interventions. The concept of actionable meaning as introduced in this thesis is closely related to *semantic computing*, which refers to "computing with (machine processable) descriptions of content and intentions" (Parastatidis, et al., 2009). The difference between semantic computing and making the substance or meaning of network data actionable is that the approach I take does not necessarily imply the consideration of intensions, but focuses on contributing to the potential practical usefulness of network data.

1.8 Summary of Contributions

The study of the impact of coding choices on network data and analysis results (chapter 2) and the implications of these findings for practical work (chapter 4.1) can help people to become better informed users of relation extraction methods and technologies, to gain greater control over these multi-step analysis procedures, and to draw reasonable conclusions from network analysis results. The findings from chapter 2 emphasize that it is crucial to know the amount and nature of the impact and interaction effects of routines involved in relation extraction on network data. This work together with the testing of the prediction quality of an entity extractor (built in chapter 3) in different applications settings (chapter 5) complements traditional accuracy assessments of relation extraction methods.

In chapter 4, the transition from experimental results for a) the impact of coding choices on network data and b) the accuracy of the entity extractor in real-world applications is described. This work increases the practical usefulness and interpretability of network analysis results. Also, the challenges identified for converting trained prediction models into ready to use software, and the developed solutions to these challenges can provide others with guidance for this kind of design and engineering process.

With the comparison of network data generated with different methods from the same corpora (chapter 5), the differences and commonalities in network structure and analysis results are

identified. Moreover, I show which findings generalize across domains and writing styles, and which ones are domain-specific. This knowledge is relevant in the context of networks for which insufficient or unreliable ground truth data are available, because in these situations, it is crucial to know how the views on networks differ depending on the relation extraction method. This work has also shown that generating thesauri by using the entity extractor built in chapters 3 and 4 greatly reduces the time costs for constructing thesauri with alternative methods. However, based on the findings from the qualitative assessment of the auto-generated thesauri, it does not seem recommendable to use these thesauri without further verification and refinements. The strategies and tools for post-processing the auto-generated thesauri that I describe and developed in chapters 4 and 5 might help others with this process. Moreover, my results show that working through this refinement process increases the similarity between networks generated by using the auto-generated thesauri and networks generated with alternative methods.

In chapter 6, an advancement to the method of enhancing social network data with content nodes extracted from text bodies is developed, operationalized and tested. This approach considers the substance of text data and helps to integrate different aspects that drive the properties and dynamics of networks. I conclude that extracting content nodes from groups of *structurally equivalent* agents is an appropriate strategy for enabling the *comparison* of the information that these agents produce, perceive or disseminate, while extracting content nodes from groups of *structurally coherent* agents is an appropriate strategy for enabling the *enhancement* of social network data with content nodes. The results from putting the latter approach to the test include a comparison of the outcome of topic modeling to the results from alternative information extraction methods, including supervised learning. My findings show that performing key player analysis on text-based networks retrieves only a small portion of entities that would not be found with topic modeling, and that entities from meta-data knowledge networks might serve as proper labels for unlabeled topics. Also, these comparisons further complement the findings from previous chapters about the differences and commonalities between various methods for constructing network data from text corpora.

In summary, by bringing together text data and relational data, this thesis makes substantial advances at the nexus of text analysis and network analysis. Using text data for network analysis is further a valuable strategy for contextualizing and interpreting graphs, and transforming linked data into useable information and knowledge (Parastatidis, et al., 2009).

2 Impact of Methodological Choices for Relation Extraction on Network Data and Social Network Analysis Results[1]

2.1 Introduction to Relation Extraction from Text Data

When network data are needed and text data are available as a source of information, network data can be extracted from texts. In computer science, this task is referred to as Relation Extraction (REX). Methods for going form texts to networks have been developed in different fields, mainly Artificial Intelligence (AI) (J. Sowa, 1992), Natural Language Processing (NLP) and Computational Linguistics (CL) (Mihalcea & Radev, 2011), social science (K.M. Carley, 1993; Glaser & Strauss, 1967) and political science (Gerner, et al., 1994). Even though these methods differ in their terminology, underlying theories and assumptions, degree of automation, evaluation strategies, and typical application areas, they overlap in that they exploit one or more of the following types of information:

- Lexical and morphological information, i.e. words and their structure (Woods, 1975).
- Syntax, i.e. the relationship between words (Janas & Schwind, 1979).
- Semantics, i.e. the meaning of words and language (C. J. Fillmore, 1968).
- Pragmatics, i.e. the social use of language (Hovy, 1990).
- Logical (Shapiro, 1971) and statistical (A. McCallum, 2005) information.

These types of information are explicitly or implicitly available in text data, or can be inferred from it. Section 4.2 provides a problem-oriented review of the families of methods for going from texts to networks. For a more comprehensive review, see also Diesner and Carley (2010). Currently, the most accurate, efficient and scalable REX methods combine NLP and CL techniques, and involve routines from statistics and machine learning (A. McCallum, 2005; Van Atteveldt, 2008).

At a minimum, REX involves three steps, which are typically performed in the following order:

1. Data preprocessing: this includes subroutines such as chunking (partitioning texts into semantic units, typically sentences) and reference resolution.
2. Node identification, and if needed node classification: the generalized version of this task has been studied in NLP and Information Extraction (IE) under the label of Named Entity Recognition (NER) (D. Bikel, M. , Schwartz, & Weischedel, 1999), and also in political

[1] In this chapter, portions of the following paper are reprinted, with permission, from: Diesner, J., & Carley, K. M. (2009). He says, she says. Pat says, Ttricia says. How much reference resolution matters for entity extraction, relation extraction, and social network analysis. Proceedings of IEEE Symposium on Computational Intelligence for Security and Defence Applications (CISDA), Ottawa, Canada, © IEEE.

science, where it is called event data coding (P. A. Schrodt, Yilmaz, Gerner, & Hermick, 2008). A more detailed introduction to this and the next step is provided in section 3.2.

3. Edge identification, and if needed edge classification: in this step, the identified nodes are linked into edges (Miller, Fox, Ramshaw, & Weischedel, 2000; Zelenko, Aone, & Richardella, 2003).

Tremendous progress in the automation and performance of REX has been achieved over the last decade (see for example Brin, 1999; R. C. Bunescu, 2007; Etzioni, et al., 2004; A McCallum, Wang, & Mohanty, 2007; Zelenko, et al., 2003). These advances are mainly due to two reasons: First, they were facilitated by REX competitions that were initiated and funded by US-American governmental agencies, such as the Message Understanding Conference (MUC) (Nancy Chinchor & Sundheim, 2003), the Automatic Content Extraction Program (ACE) (Walker, Strassel, Medero, & Maeda, 2006), and the Translingual Information Detection, Extraction and Summarization Program (TIDES) (A. Mitchell, et al., 2003). These competitions involved the provision of benchmark datasets and the development of rigorous REX evaluation metrics. Second, advances in REX have been attributed to progress with statistical and machine learning techniques, which have been developed or adopted by NLP researchers (Mihalcea & Radev, 2011).

2.2 Evaluation of Relation Extraction: Problem Statement and Research Question

Relational data extracted from texts may represent the nodes and edges in the network of interest accurately or not. In the NLP domain, accuracy is typically measured as the percentage of correctly identified and categorized entities and relations. More specifically, two common methods are available for determining the accuracy of the retrieved data:

First, the "gold standard test" compares distilled network data against ground truth data that has been previously annotated by trained human experts with entities and/or relations. The manual or computer-supported generation of correct and reliable ground truth data is expensive: humans trained for this task can identify and mark up about five to ten relations or events per hour, or up to 40 relations per day (P. Schrodt, 2001; P. A. Schrodt, et al., 2008). Fortunately, various annotated datasets for IE tasks, including NER and REX, have been generated for nationally funded initiatives and made publically available through the Linguistic Data Consortium (LDC). An overview of these datasets is provided in Table 5. However, the complex task of annotating data for REX has lead to compromises: First, most standard REX datasets denote relations mainly on the sentence level (Bond, et al., 2003). One explanation for this effect might be that the reliable identification, disambiguation and annotation of entities and relations within and

across multiple sentences, paragraphs, documents or even corpora might be cognitively too complex for humans to do (Corman, et al., 2002). Second, the number of different classes of entities, and even more so of relations, considered for REX is often kept fairly small: typically, such systems are constrained to locating and classifying entities that represent people, organizations, and locations, and that are referred to by a name. For edges, most solutions identify the existence of relationships that are defined over these node types, and sometimes classify these relations according to some predefined ontology. As a result, the workflow in many of these systems is such that entities are identified first, and edges second. In an attempt to challenging this standard procedure, Roth and Yih (2002) showed that knowing the class label of entities helps to label relations, but not vice versa. Their results confirmed the traditional sequence of steps in REX.

As an alternative to the gold standard test, REX outputs can be assessed by subject matter experts (SME). The SMEs examine how closely the extracted data resemble the actual network of interest (King & Lowe, 2003). However, for real-world applications, the obtained network data are often too voluminous and too complex to be vetted by humans for their accuracy. To make things worse, in some cases, neither any ground truth data nor SMEs are available to validate the data, e.g. when performing REX on historical data (Bearman & Stovel, 2000).

In summary, REX evaluation methods and metrics are tuned towards maximizing the accuracy of REX methods while avoiding overfitting to the training data. Here, accuracy means resemblance of the ground truth as identified by human experts. As a consequence, research efforts in this area have been focused on improving existing REX methods or developing new ones, and reporting increases in accuracy over a baseline, established benchmark value, or competing systems. Typically, the research question asked with this type of work is, in a simplified form: How can we build a method or system that leads to the comparatively most accurate relation extraction results? I argue that while answers to this question advance the field of NLP, this question does not address two additional aspects that are also crucial for understanding and improving the performance of REX solutions:

First, the steps involved in REX, i.e. preprocessing and the identification (and classification) of nodes and edges are not independent of each other. This means that the decisions made for one step can impact the results obtained from any subsequent step (H. Bernard & Ryan, 1998; K.M. Carley, 1993; C. W. Roberts, 1997b; D. Roth & Yih, 2002; S Sarawagi, 2008). This type of complexity is further increased by the fact that modern REX techniques typically comprise multiple subroutines per step, and these subroutines can also exhibit interaction effects. The problem here is that the described interdependencies can lead to cascading errors and impact on intermediate results, but we do not yet have a good understanding of these effects, their impact

on the final results, and the robustness of REX methods towards these effects. One reason for this lack of knowledge is that this research questions has not yet been raised. This is troublesome because any error throughout the REX process can lead to inaccurate network data, erroneous analysis results, and misleading interpretations. Addressing this question gains further importance as the intermediate steps involved in REX are not flawless themselves: standard pre-processing techniques that support shallow parsing, such as parts of speech tagging and reference resolution, have error rates of about 4% and 20% to 40%, respectively (Denis & Baldridge, 2007; Diesner & Carley, 2008b). For entity extraction, accuracy rates are about 80% to 90% (CoNLL-2003, 2003; MUC7, 2001). The edge identification stage will inherits these errors. Top performing relation extraction solutions have error rates of 30% up to 50% (S Sarawagi, 2008). Yet another factor contributing to the limited understanding of interdependencies and error propagation in REX is that state of the art REX systems do not necessarily expose or provide documentation on the details about all employed subroutines. Therefore, the propagation of variation in results is not always transparent or comprehensible to end users. Finally, in academic work, the process of link identification often assumes that node identification has already happened (Chang, Boyd-Graber, & Blei, 2009). This separation of tasks inhibits the investigation of end-to-end propagations of error and intermediate results.

Second, the selection of specific methods and subroutines impacts not only the accuracy of entity and relation extraction, but also the structure and properties of the retrieved data. However, the relationship between changes in the accuracy of REX and changes in network properties are also insufficiently investigated and understood. This gap in research has been previously pointed out by others (K.M. Carley, 1997a; P. Schrodt, 2001). Why would knowledge about this relationship matter? Let's assume somebody provides a new or improved algorithm that leads to a statistically significant increase in REX accuracy. This would be a substantial contribution from an NLP point of view. However, this piece of information does not tell us anything about what changes we could expect in the properties of network data and the values of network analytical metrics. If the changes in network characteristics were also significant and maybe even larger than the changes in REX accuracy, the need for more accurate REX solutions would be further substantiated, and success in achieving this goal would advance both, REX as a subfield of NLP and network analysis. If, however, these changes were insignificant, further investing in improving REX accuracy rates would not be worthwhile from a network analysis perspective.

This thesis addresses both of the shortcomings that I have identified and described above, and contributes to a more comprehensive understanding of REX accuracy by addressing the following research question: How much variation in the structure and properties of network data extracted from texts and results from analyzing these data are due to decisions made during the

REX process? This question is further specified in the methods section of this chapter. Ultimately, what we need is a comprehensive knowledge base of method-induced biases and error propagation effects for REX that everybody can draw from when applying or developing such methods. With this thesis, I get work started in this direction by investigating the impact of choices about selected and widely used text coding techniques on network data and analysis results.

Who cares about the outcome of this work? Even though most REX methods have been developed for specific domains and corpora, many of them share a large portion of routines for pre-processing and node and edge extraction. I argue that a better understanding of error propagation and the robustness of REX methods contributes to a greater comparability and generalizability of respective methods. Such knowledge would also provide developers and end-users of REX tools with greater transparency and control over complex, multi-stage analysis processes. Furthermore, a more precise understanding of the relationship between choices made for REX and the robustness of network data towards these effects helps end-users to draw valid and reasonable conclusions from their network analysis results. Also, engineers can take this knowledge into account when integrating REX solutions with network analysis technologies. Finally, an answer to the research questions raised in this chapter is particularly relevant when network data are hard to validate, because the knowledge gained with this study can help us to weight or rule out effects induced by methodological choices.

2.3 Method

How to identify the impact of methodological choices on network data? One strategy would be to conduct a series of user studies, where we observe the coding choices that people make, and ask them about the conclusions they draw from interpreting the network analysis results. The advantage with this approach is that is allows for experimenting with currently relevant domains and various genres of text data. However, collecting enough data this way such that we can generalize the findings is a costly, long term process as already outlined in section 2.2. Alternatively, one could rely on previously generated and validated benchmark datasets. This strategy offers various advantages: it is more cost efficient, does not involve additional reliability tests of the human coding, and allows me to focus on the core of my research question, i.e. the isolation of the impact of user choices on network data. Based on this comparison of strategies, I decided to use the second approach. In summary, I determine the impact of selected methodological choices about REX and the robustness of network data towards these choices by employing the following process:

1. Identify a set of relevant methodological choices to investigate (this section).

2. Find data that allow for testing the impact of these choices (section 2.6).
3. Conduct a series of controlled experiments in order to determine the impact of these choices while holding all other factors constant (section 2.7).

2.4 Reference Resolution: Background and Research Questions

Reference Resolution is a widely used pre-processing technique in information extraction and relation extraction. This technique identifies the entity that a referring expression refers to (Hobbs, 1979; Sidner, 1979). For practical applications this means that the various instances and mentions of unique entities, including pronouns, spelling variations, abbreviations, and repetitions, are identified and consistently associated with or converted into a unique key identifier per entity.

Reference resolution comprises two tasks: anaphora resolution and coreference resolution. The goal with anaphora resolution is to identify the antecedent *A* that an anaphoric expression, also known as anaphor, *B* refers to (Sidner, 1979). Typically, *A* is a noun phrase and precedes *B*, which usually is a pronoun, in the text. *A* is only considered to be an antecedent of *B* if *A* is required for resolving *B*. Thus, the relationship between *A* and *B* is non-symmetric, non-reflexive, and non-transitive (Deemter & Kibble, 2000). The goal with coreference resolution is to identify all of the entities that are mentions of the same referent *C* (Hobbs, 1979). These referring expressions are typically noun phrases. Entity *C* may or may not be explicitly mentioned in the text data. Entities *A* and *B* are only considered to be co-referents if they both unambiguously represent entity *C*, such that *A*=*C* and *B*=*C*. Therefore, coreferences are symmetric, reflexive, and transitive equivalence relationships (Deemter & Kibble, 2000).

How do anaphora resolution (AR) and coreference resolution (CR) relate to each other? If an anaphor *B* and its antecedent *A* refer to the same entity, *A* and *B* are coreferential. However, there is no deterministic or set-theoretic relationship between AR and CR, i.e. an anaphoric and a coreferential relation may overlap, but not all cases of AR are also cases of CR and vice versa. Another difference between AR and CR is that for resolving a given *B*, in AR, *A* has to be interpreted within the context of the text in which both phrases occur, while in CR, interpreting *A* is not required for testing which entity *C* a *B* is identical to. For example, in the phrase “Barack Obama, the President and Nobel Peace Prize winner…”, both mentions of a person refer to the real-world entity *C* = “Barack Obama”, but an interpretation of entity *A* (President) is not required for resolving entity *B* (winner). In contrast to that, resolving the referential expression *B* = “he” in the phrase “Obama ran for president in 2008. In 2010, he won the Nobel Peace Prize”, with “Obama” being the antecedent *A*, requires an interpretation of the text preceding *B*.

How is Reference resolution (RR) relevant for REX? Both, AR and CR, are normalization and deduplication techniques that are commonly used as pre-processing steps when performing entity extraction and relation extraction. In this context, AR is used to translate pronouns into the non-pronominal entities that the pronouns refer to. I use the terms *entity* and *node* interchangeably in this chapter since the set of entities contained in a corpus is also the set of nodes from which networks can be constructed. CR is applied to map multiple instances of an entity to one unique, non-pronominal identifier, and to associate co-referring entities with each other. Taking these effects together, RR can impact the identity, literal mention (i.e. spelling), and weight of nodes and edges. Since we do not yet know how strong these impacts are, I investigate them in this project. Furthermore, I argue that the insights gained from this study complement prior knowledge about the deduplication and consolidation of records in relational data, e.g. in relational databases (Bhattacharya & Getoor, 2007; Culotta & McCallum, 2005).

What impact can reference resolution exactly have on network data? Both, AR and CR, can increase the number of mentions per unique entities, which in network analysis is often used as the node weight, as follows: while AR does not alter the number or of unique named entities, CR potentially reduces this number. Also, while AR mainly reduces the number of pronouns, CR can only lead to this effect if a set of unresolved pronouns are identified as being co-referring to each other. Table 3 summarizes these possible effects. The cells labeled as "yes" in Table 3 represent the desired outcome of performing RR.

Table 3: Applicability and Impact of Reference Resolution Methods

Case	Type of entity		Applicability of Reference Resolution methods		Potential impact on unique entities (names or nominals, not pronouns)	
	Name or Nominal	Pronoun	Anaphora Resolution	Coreference Resolution	Number	Weight of impacted entities
1	N=1	0	not applicable	not applicable	n.a.	n.a.
2	0	N=1	not applicable	not possible	n.a.	n.a.
3	N>1	0	not applicable	yes	decrease	increase
4	0	N>1	not possible	yes†	none*	none**
5	N=1	N >= 1	yes	yes†	none	increase
6	N>1	N >= 1	yes	yes	decrease	increase

† Only among pronouns if number of pronouns > 1

* Decrease of number of distinct pronouns possible

** Increase of weight of unique pronouns

For links, the resolution of anaphoric node names does not change the link weight. If however two nodes *A* and *B* in a link are coreferences of two nodes *C* and *D* in another link such that *A*=*C* and *B*=*D* or *A*=*D* and *B*=*C*, these two links can be merged into one link while increasing the link

weight by one. If further links are merged into this link, the link weight is increased accordingly. In summary, conducting AR and CR on the entity level is a precondition for impacts of RR on the relation extraction and network analysis level.

In summary, RR can have the following impact on network data: AR decreases the number of pronominal entities. CR decreases the number of unassociated entities and relations. As a result, both, AR and CR, increase the number of mentions of unique, non-pronominal entities. If these entities appear as nodes in a network, including isolated nodes, the weight of nodes and of links can be increased, and the number of links can be decreased. Combining AR and CR might be more effective in achieving these effects than either technique alone.

Current RR techniques achieve accuracy rates of less than 100%, and no algorithm might ever return perfectly correct reference resolution results. In NLP, accuracy is typically measured in terms recall, precision and accuracy. These measures are defined below. Recall measures coverage, i.e. what percentage of entities or links that occur in the ground truth data have been retrieved. Precision measures accuracy, i.e. what percentage of the retrieved items, which often include false positives, are correct ones, i.e. occur in the ground truth data. Since recall and precision are typically inversely related, the harmonic mean of both values is also computed, which is called the F-measure.

Equation 1

$$Recall = \frac{number\ of\ correctly\ classified\ entities\ retrieved}{number\ of\ entities\ in\ ground\ truth}$$

Equation 2

$$Precision = \frac{number\ of\ correctly\ classified\ entities\ retrieved}{number\ of\ entities\ retrieved}$$

Equation 3

$$F = \frac{Recall * Precision}{0.5(\ Recall + Precision)}$$

Actual accuracy rates for RR depend strongly on the applied resolution method, data set, and evaluation metrics. Table 4 gives an overview on selected performance results; showing that state of the art accuracy rates are about 80% and more for AR, and about 70% for CR. The top scoring techniques are based on supervised machine learning methods. In this study, I simulate the introduction of typical errors into ground truth data in order to understand how much change in RR accuracy leads to what changes in network properties.

Table 4: Selection of accuracy rates for Reference Resolution

System	RR	Training data	Evaluation Metric	Recall	Pre-cision	F
Reconcile (Stoyanov, et al.)	CR	ACE5	B cubed	55	65	60
Illinois Coreference Package (Bengtson & Roth, 2008), Stanford Deterministic Coreference Resolution System (Raghunathan, et al., 2010)	CR, AR and CR	ACE4	B cubed	75	88	81
SemEval2010 (English, information: open, annotation: gold) various participants (Recasens, et al.)	CR	SemEval OntoNotes	B cubed	75-85	78-97	82-85
BART (Versley, et al., 2008)	AR, CR	ACE2	n.a., B cubed?	55	78	64

My overall research question for this project is: What impact does reference resolution have on network data and network properties? I have already shown in the introduction section that both, AR and CR, can lead to an increase in the number of mentions per unique, non-pronominal entity and in the weight of nodes and links, and a decrease in the number of links. Since the goal with this project is to understand the impact of reference resolution on nodes, links, and network data, I am asking the same research questions on the level of entities, links, and network data analysis. Based on the presented relationship between reference resolution and network analysis, and the logic and functioning of RR techniques, I address the following research questions herein:

Question 1: How large are these effects on the entity level? Which routine, AR or CR, is more effective in achieving these effects? Is combining AR and CR more effective than either technique alone?

Answers to the first research question are relevant when conducting NER and content analysis, and for preparing nodes for the construction of network data, for example.

Question 2: How large are these effects on the link level? Which routine, AR or CR, is more effective in achieving these effects? Is combining AR and CR more effective than either technique alone?

Question 3: How large are these effects on the network level? Which routine, AR or CR, is more effective in achieving these effects? Is combining AR and CR more effective than either technique alone?

Answering these research questions is relevant when performing relation extraction.

Question 4: How much change in network properties in due to increases in accuracy of AR and CR?

Answers this research question is relevant for selecting a RR technique that is appropriate given the type of network analysis that one plans to conduct.

2.5 Windowing: Background and Research Questions

Once nodes have been identified via entity extraction or some alternative technique, they can be linked into edges in order to construct network data. For this purpose, a variety of approaches have been developed, which exploit lexical (Gerner, et al., 1994), semantic (Woods, 1975), syntactic (D. Roth & Yih, 2007), logical (Berners-Lee, Hendler, & Lassila, 2001; Woods, 1975), taxonomic and ontological (Fellbaum, 1998), and proximal (J. A. Danowski, 1993) information from text data. A summary of the main methods that use these link formation approaches is provided in Table 52. For a more detailed review see also Diesner & Carley (J. Diesner & K. Carley, 2010).

Especially in the domain of network text analysis, a commonly used link formation approach is windowing (K.M. Carley, 1993; J. A. Danowski, 1993). Windowing is a proximity based approach that basically links all entities within a user-defined portion of the text data into edges. Parameters of the window are the chunk of the text input, e.g. sentences or paragraphs, and the number of adjacent words. With some approaches, all identified entities within each chunk or sentence are linked together (Corman, et al., 2002; Gerner, et al., 1994). In other approaches, connections are only permitted between certain types of nodes (links defined over node types) or nodes that have a specific relationship with each other (typically the case for syntactic relation).

The advantages with windowing are that the technique is easy to implement, to adopt for new domains, and to comprehend for end users. These reasons might explain the frequent use of this approach for practical applications. The main critique[2] of windowing is that it is fairly arbitrary and not grounded in theory or any assumption about text production and comprehension (Corman, et al., 2002). Moreover, there are hardly any empiric studies of appropriate window sizes which could guide the selection of a suitable window. I tackle this issue by addressing the following research questions:

1. What window sizes do human experts use when identifying relations in text data? Does the typical window size differ depending on the type of data or relations?
2. What window size is needed to capture the vast majority of links in text data? Does this window size differ depending on the type of data or relations?

[2] One critique that we have often received on papers that we had submitted and where we used text coding in AutoMap was that the choice of a certain window size was not well justified. One goal with this project is to harness this point of critique.

3. What error rate, i.e. amount of wrongfully identified links (false positives) and missed links (false negatives), can be expected when applying a specific window size? Does the error rate differ depending on the type of data or relations?

2.6 Data

For this project, I do not conduct references resolution and windowing manually or algorithmically, but work with sizable datasets that trained human coders have annotated for these tasks. These datasets are assumed to be gold-standard, ground truth data, for which the intercoder-reliability and annotation quality have been previously validated (Jurafsky & Martin, 2000). Using these data allows me to make non-probabilistic statements about the impact of the investigated techniques; thus providing an empirically grounded benchmark for the impact of reference resolution techniques and windowing on relational data. Table 5 provides an overview of these datasets, and compares them along a few dimensions. These dimensions are relevant for choosing appropriate datasets for the projects presented herein, and show what types of data my findings can reasonably be assumed to generalize to. Table 152 in the Appendix lists the full name and provider ID for each of these datasets.

Table 5: Overview on eligible datasets for the information extraction and relation extraction projects in chapters 3 and 4*

Short name	Full name	Enti-ties	Relati ons	Co-Ref.	Ana-phora	Genre **	Size	Year ***	Used in thesis
MUC 6	(Nancy Chinchor & Sundheim, 2003)	x		x	x (only if coref)	nw (WSJ)	318 articles	1986-1994, 2003	no
MUC 7	(N. Chinchor & Sundheim, 2001)	x	x	x	x (only if coref)	nw (NYT)	225 articles	1996, 2001	no
ACE 2	(A. Mitchell, et al., 2003)	x	x	x	x	news, nw, bcn, ms	518 files	1998, 2003	Ref. Res. (chapter 3)
TIDES 2003	(A. Mitchell, et al., 2003)	x	x	x	x	nw, bcn, sp, ms	252 files	2000, 2003	no
ACE 2004	(A. Mitchell, Strassel, Huang, & Zakhary, 2005)	x	x	x	x	nw, bcn, ms	599 files	2000, 2005	no
ACE 2005	(Walker, et al., 2006)	x	x	x	x	nw, bcn, bcc, ng, weblogs, ms	599 files	2000-2003, 2006	Ref. Res. and Windowing (chapter 3)

reACE	(Hachey, Grover, & Tobin, 2006)	x	x	x	x	ACE 2004, ACE 2005, BioInfer	900 files (estimate)	2000-2006, 2011	no
BBN	(Weischedel & Brunstein, 2005)	x			x	nw (WSJ)	2454 articles	1989, 2005	Entity Extraction (chapter 4)
Sem Eval 2010-8	(Hendrickx, Kim, Kozareva, & Nakov, 2009)	x (untyped)	x			from the web	10718 examples	n.a.	Windowing (chapter 3)
Onto Notes 4	(Weischedel, et al., 2011)	x		x		nw, bcn, bcc, ng, web data, ms	353 files (estimate)	2006, 2011	no
Sem Eval 2010-1	(Recasens, et al.)	x		x		see OntoNotes 4	353 files	2006, 2010	no
NYT AC	(Sandhaus, 2008)	x		x		nw (NYT)	1.5 Mio. Articles	1987-2007, 2008	no
CoNLL 2003	(CoNLL-2003, 2003)	x				nw, Reuters corpus	1393 files	1996-1997, 2000	no

* only English text data considered herein

** nw = newswire, bcc = broadcast conversations, bcn = broadcast news, sp = speech, ng = newgroups, ms = from multiple sources (not genres, but different news paper for example)

***first number: source (English), second number: data source provider

For the reference resolution project, data are needed in which sufficiently large amounts of anaphoric relations, coreferential relations, and other types of relations between entities are annotated. Eligible data sets are MUC and ACE (incl. TIDES and reACE) (Table 5). In MUC, however, relations are restricted to specific types of links between entities and organizations only, and the total number of marked up relations (N = 800) is lower by factor of ten than in ACE (Table 6). For these reasons, MUC was not selected for this project. Given that all ACE datasets would be appropriate for this project based on their size and breadth of types of relations considered, I choose to use the oldest (ACE2) and newest (ACE5) one outlined in Table 5. The reason for this decision is that it allows for testing whether findings are robust over time (the difference in publishing date of the articles in these corpora is five years). Furthermore, ACE 2 and ACE 5 are similar in the amount and type of annotated relations, thus enabling reasonable comparisons (Table 6). They also overlap in genre - both cover printed and spoken news data – which again facilitates comparisons across time. In addition to that, ACE covers three additional

genres, namely blogs, online discussion groups, and telephone conversations, which allows for testing differences between genres.

For the windowing project, I was looking for data in which large numbers of examples for different types of relationships are marked up, so that the robustness of findings across differences types of relations can be assessed. Table 6 provides a comparison of the number of types of relations per corpus. In order to provide consistency in this chapter, I choose to use ACE5 for this project again. From all of the various ACE datasets, ACE5 offers the greatest variety of genres and types of relations to analyze (syntactic, semantic, relations defined over node types). As I am also aiming for generalizability of the findings from this study, it seemed important to find a different point of comparison, i.e. not ACE2, since the annotation guideless for establishing relations are very similar for ACE2 and ACE5 (in fact, they were developed over time from the same baseline). The only dataset that fulfills these criteria is SemEval, and it was therefore was chosen for the windowing project.

Table 6: Comparison of relations in datasets

Size of dataset and comments	Types of relations considered
MUC 7 N = 800 relations between entities and organizations only	1. Employee of 2. Product of 3. Location of
ACE 2, TIDES N = 8,127 all defined over entity types further classifications: class: explicit, implicit	1. Role: employment (management, general staff), other (member, owner, founder, client, affiliate-partner, citizen-of, other) 2. Part: subsidiary, part-of, other 3. At: located, based in, residence 4. Near: relative location 5. Social: personal (parent, sibling, spouse, grandparent, other relative, other personal), professional (associate, other profess.)
ACE 2004 some defined over entity types	1. Physical: located, near, part whole 2. Personal/Social: business, family, other 3. Employment/Membership/Subsidiary: employ-exec(s), employ-staff, employ-undetermined, member of group, subsidiary, partner, other 4. Agent-Artifact: user/owner, inventor/ manufacturer, other 5. Person-Organization: ethnic, ideology, other 6. GPE Affiliation: citizen/resident, based in, other 7. Discourse
ACE 2005 N = 8,738 all defined over entity types further classifications: syntactic relation, modality,	1. Physical: located, near 2. Part whole: geographical, subsidiary, artifact 3. Personal/ social: business, family, lasting-personal 4. ORG Affiliations: employment, ownership, founder, student-alum, sports-affiliation, investor-shareholder, membership

tense	5. Agent-Artifact: user-owner- inventor-manufacturer 6. Gen-Affiliation: citizen-resident-religion-ethnicity, org-location-
SemEval 2010-8 N = 10,717 not defined over entity types, entity types not labeled	1. Cause-Effect 2. Component-Whole 3. Content-Container 4. Entity-Destination 5. Entity-Origin 6. Instrument-Agency 7. Member-Collection 8. Message-Topic 9. Other 10. Product-Producer

2.6.1 Preparing Datasets for Experiments

The datasets selected for this project use different ways of marking up entities, relations, and other text properties that are needed for this project. Therefore, I built a parser for each datasets in order to extract the information needed. I briefly describe the details on this process to the minimum extent needed for ensuring the reproducibility of my results.

In ACE, the text files are marked up in SGML format. These files contain only the raw texts and meta-data, such as the source and release date of an article. The information on entities and relations is specified in XML files. In these files, entities and relations have a head (key word or key phrase) and an extent (typically a nominal phrase). The mapping from the XML files to the text files is realized through position numbers. This numbering pauses at SGML tags within the body. I consider elements of the types "entity" and "timex" as entities. Entities of the type "timex" are considered herein because they represent instances of the "time" class in the meta-network model. The meta-network model is a theoretically grounded model of relevant classes of entities and links in socio-technical networks (for a more detailed description see section 3.2.4). The mentions of entities in the data are categorized as names, nominals or pronouns. Pronouns include terms like "one", "some" and "there".

In ACE, the "smallest or closest possible relation" is tagged, typically on the sentence level (Consortium, 2008). A few relations span across sentences. In general, analyzing gold standard information about window sizes across sentences would contribute new knowledge, but since this option violates the preferred norms in ACE, I did not further explore this path.

Relations are coded as follows in ACE: if two entity mentions *C* and *D*, which are instances of a pair of nodes that involves entity mentions *A* and *B* such that *A*=*C* and *B*=*D* or *A*=*D* and *B*=*C* are identified to form the same type of relationship, the respective relationship is annotated to have multiple mentions (in this case two). If the type of relationships is different, the relations are

marked up as different relations. In order to identify the impact of CR on relational data, I deviate from this notion of link identity by using the following operationalization: any two links that were marked up in a given text are identical if both entity mentions in one link map to the same entities as the entity mentions in another link.

Finally, ACE2 contains 20 redundant relations (same type of relationship between identical nodes at same text position), which I deduplicated. ACE 2005 contains four relations where the head of both nodes were identical (same token at same position in same file). In network terms, such links are called loops, and are legitimate network constituents. I disregarded these four relations for the entity level analysis since they would dilute the coreference resolution results (even though the impact is minimal), but kept them for the relation and network level analysis.

2.6.2 Selection of Relevant Aspects of Relational Data for Analysis

The ACE data have been previously used by others to develop and validate cutting-edge reference resolution techniques (Doddington, et al., 2004). Both selected ACE dataset allow for studying the impact of reference resolution and windowing on multiple aspects of relational data. These aspects include the type or genre of the data, the class of nodes, such as agents or organizations, and the type of relations, such as different semantic relations. Therefore, a selection of aspects that are relevant for the context of this thesis is necessary. For the RR project, I have already explained why analyses will be conducted on the level of nodes, links, and network data. For windowing, this choice is inapplicable as windowing only impacts the network data level, and analysis are presented on this level. Moreover, for the windowing study, multiple aspects of relations that are relevant for network analysis are being considered, namely the genre of the data and the type of nodes and links. Given that for the RR project, I decided to conduct analysis on the entity, link and network data level, this comprehensive scope needed to be limited. For practical text analysis projects, a first yet unanswered question that we often face is (K. M. Carley, et al., 2007; Dabbish, et al., 2011): What coding choices would be appropriate for some specific type of data? For example, when analyzing well-formed news data, different choices and techniques might be appropriate than when analyzing data from social networking platforms, which often follow a more informal orthography and grammar. Therefore, I decided to test the impact of RR techniques on different genres. Table 7 compares the genres available in ACE with respect to the number of agents involved in producing a piece of text data, whether the text comes from written or spoken language, and the level of formality. ACE2 covers the first two genres presented in Table 7, and ACE5 covers all of them.

Table 7: Characteristics of data per genre (ACE)

Levels of compare-son between genres		Newswire	Broadcast news	Broadcast conversat.	Telephone	Usenet	Weblogs
Number of agents	Conversation			x		x	x
	Dialogue				x		x
	Monologue	x	x				x
Mode	Written	x				x	x
	Spoken		x	x	x		
Style	Formal	x	x	x			
	Informal				x	x	x

2.7 Results

The presented results are based on the judgment of trained people who aimed to deliver the best reference resolution and windowing results that humans can possibly provide. Therefore, my findings report on the upper bound of the impact of highly accurate reference resolution on entity extraction, relation extraction, and network analysis.

2.7.1 Reference Resolution

In general, two strategies are available for analyzing the impact of reference resolution on nodes, edges and network data: first, one could use only the entities that are involved in relations. Second, the full set of entities marked up in the corpus could be used. I chose the second strategy for the following reasons: first, even if an entity is not involved in a link, it might still show up as an isolated node in a graph. In fact, in network analysis, people consider isolates for certain analysis, e.g. in the context of organizational networks and networks (Klerks, 2001). The metric of "connectedness" was developed to measure the ratio of isolates in a network (Wasserman & Faust, 1994). Second, whether a node is connected into a link or not strongly depends on the mechanism for link creation; with some techniques being more inclusive than others (see sections 0 and 3.2.3 for details on methods for link creation). Third, it is possible that an isolated node gets mapped onto another, already connected node via reference resolution techniques such that the weight of the linked node is increased. In order to provide a comprehensive understanding of the upper bound of the impact of reference resolution on relational data, I decided to analyze the entire base of potential nodes.

The distribution of names, nominals and pronouns per genre (Figure 3, Figure 4[3]) shows that written newsdata data are atypical in their frequent use of names and less frequent use of

[3] Note that Figure 3 represents the same information as Figure 4 and Figure 5 together, but since there are more genres in ACE5 (Figure 4, Figure 5), I had to split up the information into two graphics to avoid overcrowding.

pronouns. Therefore, in comparison across genres, AR seems potentially least effective for news data, and can have a higher impact on all accounts of informal writing and spoken language, especially telephone conversations. The information presented in Figure 3 and Figure 4 also shows that when working with news data only (ACE2), a biased perception of the distribution of entity types emerges, which could underestimate the role of pronouns and thus AR, and overestimate the weight of names and nominals and thus the impact of CR.

The ratio of first mentions of unique entities to additional entity mentions is fairly similar across genres (Figure 3, Figure 5). Repeated references to previously introduced concepts are most prevalent among pronouns: on average, about 2/3 of pronoun mentions are back-references. This further stresses the importance of AR. Also, this finding suggest that while pronouns are typically thought of as candidates for AR, it could be worthwhile to also apply CR to them, especially if no name or nominal is available that could serve as an antecedent. The ratio of first mentions to repetitions is inverse for nominals (over 2/3 are unique, first time mentions). For names, well over half of all mentions are references to previously introduced entities.

Figure 3: Distribution of entity types (mentions) per genre (ACE2)

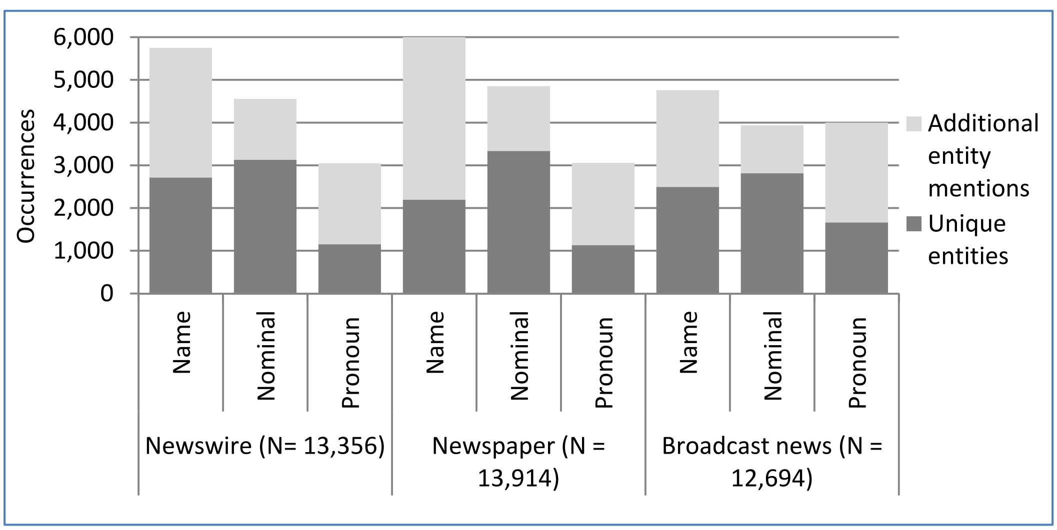


Figure 4: Distribution of entity types (mentions) per genre (ACE5)

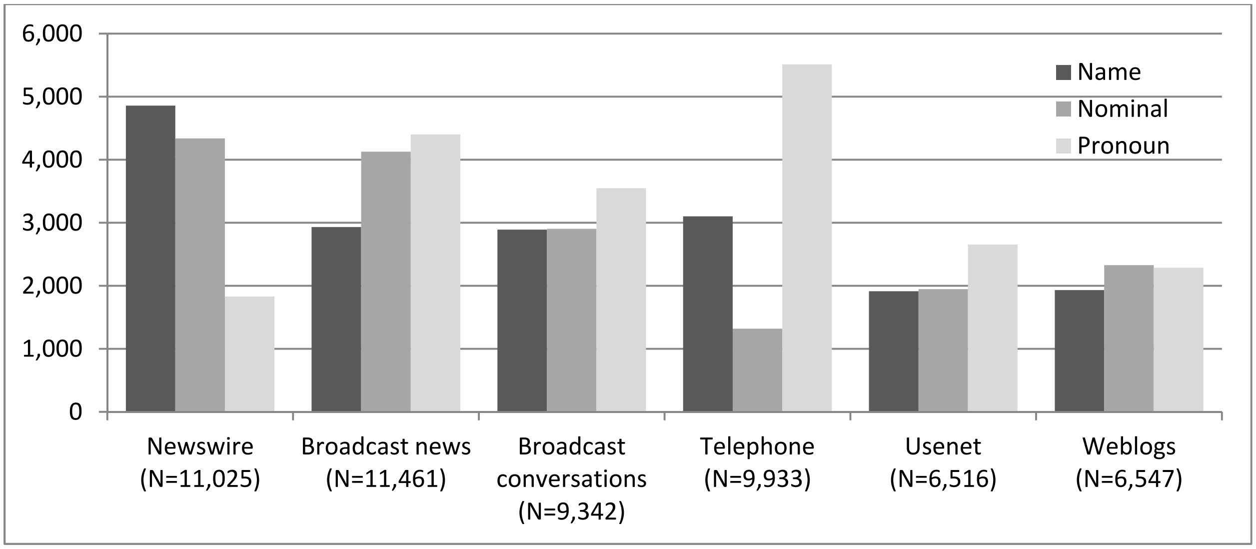
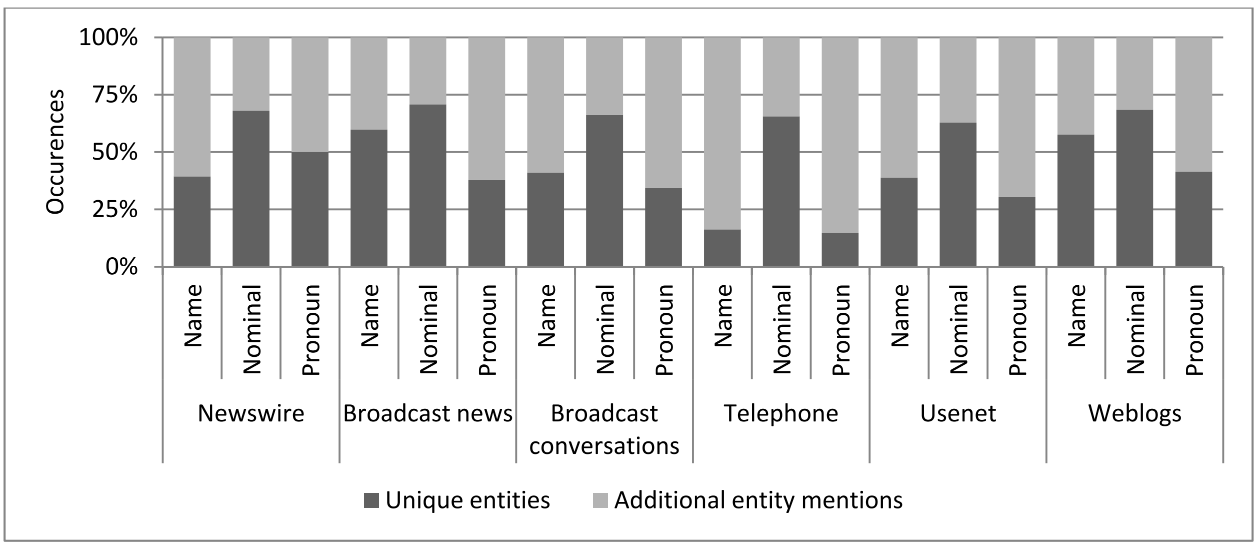


Figure 5: Ratio of unique entities and their additional mentions by entity type and genre (ACE5)



2.7.1.1 *Impact of Reference Resolution on Entities*

Depending on the genre, about 60% and more of all entity mentions are subject to reference resolution (Figure 6, Figure 7). More specifically, pronouns account for roughly 40% of all entities mentions (less than 30% for newswire and newspaper data, over than 50% for telephone data). These entities are subject to AR. Depending on the genre, additional mentions of unique names and nominals constitute another 20% to 30% of the data (40% to 50% for news data). These entities are subject to CR. Given the distributions of entity types, theoretically, AR can

make a bigger difference than CR in altering the identity and weight of nodes for six of the nine genres considered.

Figure 6: Entity mentions that are subject to change or not (ACE2)

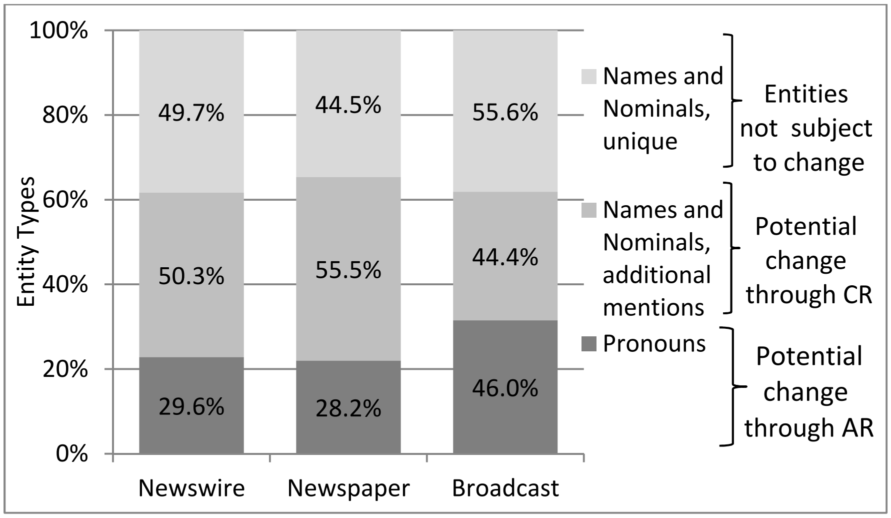
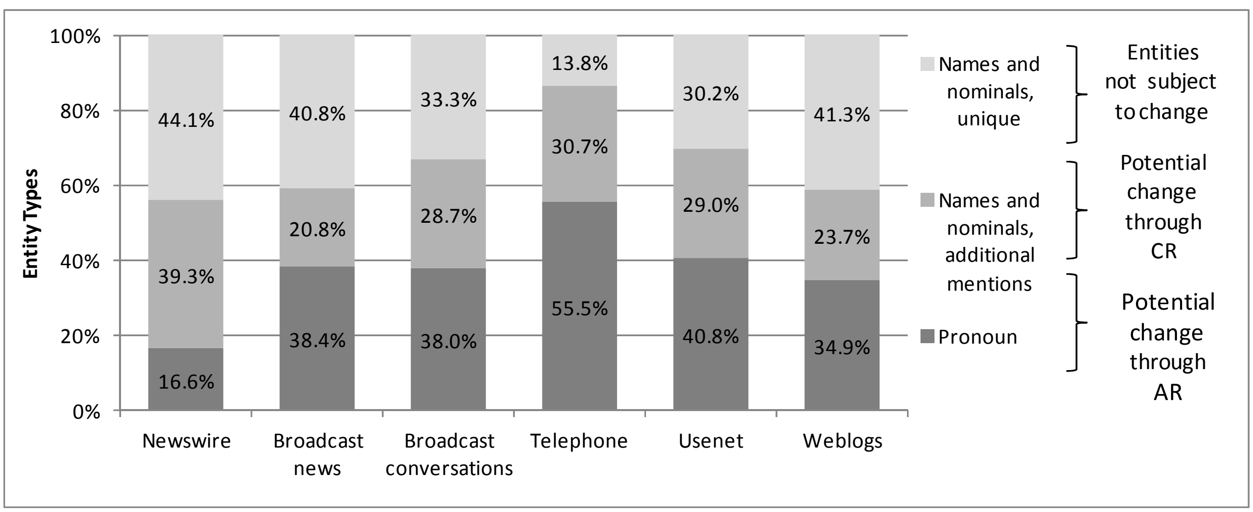


Figure 7: Entity mentions that are subject to change or not (ACE5)



In this project, anaphors are considered as irresolvable via AR only if all mentions of a pronoun are also pronouns. The results for AR show that for all genres, the majority of pronouns can be resolved (between 67% and 86%), resolution rates are higher for written texts than for spoken language, and the highest resolution rates are achieved where the ratio of pronouns is lowest (newswire, newspaper data) (Table 8, Table 9). I speculate that for transcripts of spoken language, AR is complicated by the fact that these data have proportionally more pronouns to begin with, and that therefore a smaller pool of names and nominals is available to associate the

pronouns with. Most anaphora are resolved by both, names and nominals. This indicates that conducting CR after AR is another crucial step. Nominals are slightly more effective in leading to this effect than names. This suggests that the availability of entities that are not referred to by a name, such as role descriptors, facilitates the RR process, which is important with respect to the selection of nodes classes for entity extraction in section 3.2.5. More than 65% of all irresolvable pronouns (except for telephone data, where it is 46%) are pronouns that have only one mention. They will remain in the data the way they are; accounting for 2% to 14% of all entities per genre. The unresolved pronouns that have multiple mentions can be grouped into clusters per unique entity. This grouping is done via CR.

Table 8: Results for anaphora resolution per genre (ACE2)

	Newswire	Newspaper	Broadcast news
	Unique entities		
Resolved by name(s) only	15.2%	13.6%	17.9%
Resolved by nominal(s) only	28.5%	30.2%	23.9%
Res. by both only	26.6%	29.1%	15.9%
Sum resolved	70.3%	72.9%	57.7%
Unresolved	29.7%	27.1%	42.3%
Single mentions in unres.	78.3%	76.9%	65.6%
	Entity mentions (including first mention)		
Resolved by name(s) only	12.1%	10.8%	15.7%
Resolved by nominal(s) only	19.1%	17.5%	18.5%
Resolved by both only nominal(s)	51.8%	57.0%	32.7%
Sum resolved	82.9%	85.4%	66.9%
Unresolved	17.1%	14.6%	33.1%
Resolved anaphora in corpus	18.9%	18.8%	21.3%
Irresolvable anaphora in corpus	3.9%	3.2%	10.4%

Table 9: Results for anaphora resolution per genre (ACE5)

	Newswire	Broadcast news	Broadcast conversat.	Telephone	Usenet	Weblogs
	Unique entities					
Resolved by name(s) only	9.3%	13.3%	14.2%	16.5%	23.0%	18.1%
Resolved by nominal(s) only	32.5%	28.5%	31.0%	26.4%	27.7%	34.5%
Res. by both only	34.8%	17.2%	17.7%	13.4%	10.3%	21.5%
Sum resolved	76.5%	59.1%	62.9%	56.3%	61.0%	74.1%
Unresolved	23.5%	40.9%	37.1%	43.7%	39.0%	25.9%
Single mentions in unres.	84.7%	62.7%	65.3%	46.3%	65.4%	70.3%
	Entity mentions (including first mention)					
Resolved by name(s) only	11.1%	12.1%	14.2%	34.8%	28.0%	25.4%
Resolved by nominal(s) only	23.9%	23.6%	25.1%	13.1%	25.7%	21.6%
Resolved by both only	50.7%	33.1%	34.0%	26.1%	22.6%	33.1%
Sum resolved	85.8%	68.8%	73.3%	74.0%	76.4%	80.1%

Unresolved	14.2%	31.2%	26.7%	26.0%	23.6%	19.9%
Resolved anaph. in corpus	14.2%	26.4%	27.9%	41.1%	31.1%	28.0%
Irres. anaphora in corpus	2.4%	12.0%	10.1%	14.4%	9.6%	6.9%

The results for CR show that about 30% to 40% (only 17% for telephone) of all names and nominals together are single mentions. They cannot be co-referenced by other names and nominals. Overall, most co-referencing happens via a mixture of names and nominals. This ratio of single mentions is about twice as high for nominals than for names, which does not reflect the distribution of entities in the data (there are typically more or as many names than nominals); suggesting that named entities play are more prevalent role in all genres. Single mentions of names and nominals can serve as antecedents for AR (Table 10, Table 11). Applying CR to unresolved anaphora helps to group more than 2/3 of all pronouns into clusters that refer to the same entity (Table 12, Table 13).

Table 10: Results for co-reference resolution by genre (ACE2)

	Newswire	Newspaper	Broadcast
	Unique entities		
Single Names	27.4%	21.5%	27.5%
Single Nominals	38.6%	46.5%	41.2%
Name co-ref. by Name	11.5%	9.4%	14.1%
Nominal co-ref. by Nom.	8.3%	8.0%	7.4%
Mixed co-referencing	14.2%	14.6%	9.8%
Sum singles	66.0%	68.0%	68.6%
Sum co-referenced	34.0%	32.0%	31.4%
	Entity mentions (including first mention)		
Single Name	13.6%	9.6%	15.2%
Single Nominal	19.2%	20.7%	22.8%
Name co-ref. by Name	19.1%	15.8%	21.9%
Nominal co-ref. by Nom.	12.1%	10.6%	11.0%
Mixed co-referencing	36.0%	43.4%	29.0%
Sum singles	32.8%	30.2%	38.0%
Sum co-referenced	67.2%	69.8%	62.0%
Sum co-ref. in corpus	51.9%	54.4%	42.4%

Table 11: Results for co-reference resolution by genre (ACE5)

	Newswire	Broadcast news	Broadcast conversat.	Telephone	Usenet	Weblogs
	Unique entities					
Single Names	18.9%	22.2%	18.8%	16.3%	21.3%	26.9%
Single Nominals	43.0%	47.4%	45.9%	44.1%	45.9%	43.5%
Name co-ref. by Name	8.4%	7.4%	11.9%	13.5%	12.8%	6.9%
Nominal co-ref. by Nom.	9.9%	10.3%	11.3%	14.8%	12.8%	10.1%
Mixed co-referencing	19.8%	12.6%	12.0%	11.3%	7.3%	12.5%

Sum singles	61.9%	69.6%	64.8%	60.4%	67.1%	70.4%
Sum co-referenced	38.1%	30.4%	35.2%	39.6%	32.9%	29.6%
	Entity mentions (including first mention)					
Single Name	8.4%	13.1%	9.0%	4.5%	9.9%	15.2%
Single Nominal	19.0%	27.9%	22.0%	12.3%	22.3%	24.6%
Name co-ref. by Name	16.9%	11.6%	20.6%	45.5%	22.3%	11.5%
Nominal co-ref. by Nom.	13.5%	16.4%	14.8%	11.5%	19.9%	15.8%
Mixed co-referencing	42.2%	31.0%	33.5%	26.1%	25.5%	32.9%
Sum singles	27.3%	41.0%	31.0%	16.9%	32.3%	39.8%
Sum co-referenced	72.7%	59.0%	69.0%	83.1%	67.7%	60.2%
Sum co-ref. in corpus	36.2%	36.4%	71.5%	37.0%	40.1%	39.2%

Putting the results for AR and CR on the entity level together shows that these reference resolution techniques can alter the identity and weight of at least 70% of all entity mentions (Table 12, Table 13). Entities that are not changed by reference resolution techniques are either irresolvable pronouns (less than 4% of all entities), or names and nominals that are mentioned only once, which might still be essential for AR (about 15% to 26% of all entities). I had shown that AR could have a stronger impact on entities than CR. However, the results indicate that CR contributes more strongly to the desired entity normalization and consolidation effects for all but the telephone data. One explanation for this result might be the fact that AR increases the set of entities applicable to CR in the first place. Another interesting finding here is that CR on pronouns that could not be resolved via AR has a minor yet meaningful impact on the data (less than 1% up to 13% of all entities in the resulting data). Finally, the results show that combining AR and CR is more effective than either technique alone.

Table 12: Summary of effectiveness of reference resolution techniques by genre (entity mentions, ACE2)

	Reference Resolution technique	Newswire	News-paper	Broadcast news
Anaphora	Resolved with AR	18.9%	18.8%	21.1%
	Resolved with CR	1.9%	1.5%	6.8%
	Unresolved	2.0%	1.7%	3.6%
Names & Nominals	CR	51.9%	54.4%	42.4%
	No CR	25.3%	23.6%	26.1%
Summary	Change through AR	20.8%	20.3%	27.9%
	Change through CR	51.9%	54.4%	42.4%
	Change through RR	72.7%	74.7%	70.3%

Table 13: Summary of effectiveness of reference resolution techniques by genre (entity mentions, ACE5)

Impact on	Reference Resolution technique	News-wire	Broadc. news	Broadc. convers.	Tele-phone	Usenet	Weblogs
Anaphora	Resolved with AR	14.2%	26.4%	27.9%	41.1%	31.1%	28.0%
	Resolved with CR	0.7%	8.2%	7.0%	12.8%	6.5%	4.0%
	Unresolved	1.7%	3.7%	3.2%	1.7%	3.2%	2.9%
Names & Nominals	CR	60.6%	36.4%	42.8%	37.0%	40.1%	39.2%
	No CR	22.8%	25.2%	19.2%	7.5%	19.1%	25.9%
Summary	Change through AR	14.9%	34.7%	34.8%	53.8%	37.6%	32.0%
	Change through CR	60.6%	36.4%	42.8%	37.0%	40.1%	39.2%
	Change through RR	75.5%	71.0%	77.6%	90.8%	77.7%	71.2%

In the raw set of all entities, the weight of each distinct entity mention equals one. This deviates a bit from common procedure in practical entity extraction and REX applications, where orthographically identical entities are sometimes considered to represent the same concept. When applying thesauri in AutoMap, for example, all identically spelled concept – regardless of capitalization – are translated into the same entity. This procedure greatly eases the efforts required for building thesauri, but implies the danger of false positives, e.g. in the case of homographs and heteronyms, and of false negatives, e.g. in the case of synonyms. Does the separation of identical terms from heteronyms matter with respect to entity weights? Mapping entities onto each other not based on spelling, but according to reference resolution techniques shows that for the unique entities affected by this procedure, the average node weight is increased from 1.0 to 5.1 with AR, to 4.6 with CR, and to 6.0 when using both techniques. Consequently, a significant portion of the total node weight in the dataset shifts to these entities: using both, AR and CR, makes less than 20% of the unique entities carry more than 75% of the total node weight, while the remaining more than 80% of unique entities carry less than 25% of the total weight. This means that reliable reference resolution help not only to disambiguate entities, but also to increase and enrich the amount of information available on truly distinct entities. This is particularly valuable when working with sparse networks, and sparseness is common feature of large-scale, real-world networks (Barabási & Albert, 1999).

Table 14: Comparison of impact of reference resolution techniques on entity reduction and node weights (ACE2, averaged across genres)

	Decrease in no. of unique entities (corpus)	Entities impacted by routine			Entities not impacted by routine (node weight = 1)	
		Amount	Total node weight carried	Average node weight	Amount	Total node weight carried
AR	19.56%	8.1%	26.0%	4.01	91.9%	74.0%
CR on pronouns	2.35%	1.0%	3.3%	3.42	99.0%	96.7%
CR	37.72%	19.3%	49.8%	4.13	80.7%	50.2%
AR and CR	59.63%	38.0%	74.9%	4.89	62.0%	25.1%

Table 15: Comparison of impact of reference resolution techniques on entity reduction and node weights (ACE5)

Genre	Decrease in no. of unique entities (corpus)	Entities impacted by routine			Entities not impacted by routine (node weight = 1)	
		Amount	Total node weight carried	Average node weight	Amount	Total node weight carried
	AR					
Newswire	14.2%	6.3%	20.6%	3.2	93.7%	79.4%
Broadcast news	26.4%	8.6%	35.0%	4.1	91.4%	65.0%
Broadcast con.	27.9%	8.2%	36.1%	4.4	91.8%	63.9%
Telephone	41.1%	4.6%	45.7%	9.9	95.4%	54.3%
Usenet	31.1%	7.6%	38.7%	5.1	92.4%	61.3%
Weblogs	27.4%	9.5%	36.9%	3.9	90.5%	63.1%
Average	28.0%	7.5%	35.5%	5.1	92.5%	64.5%
	CR on pronouns					
Newswire	0.4%	0.3%	0.7%	2.4	99.7%	99.3%
Broadcast news	6.0%	2.2%	8.2%	3.7	97.8%	91.8%
Broadcast con.	5.3%	1.7%	7.0%	4.1	98.3%	93.0%
Telephone	10.9%	1.9%	12.8%	6.6	98.1%	87.2%
Usenet	4.8%	1.7%	6.5%	3.9	98.3%	93.5%
Weblogs	1.0%	1.5%	2.5%	1.7	98.5%	97.5%
Average	4.7%	1.6%	6.3%	3.7	98.5%	93.7%
	CR (Names and Nominals)					
Newswire	46.6%	14.0%	60.6%	4.3	86.0%	39.4%
Broadcast news	25.4%	11.0%	36.4%	3.3	89.0%	63.6%
Broadcast con.	32.3%	10.5%	42.8%	4.1	89.5%	57.2%
Telephone	32.1%	4.9%	37.0%	7.5	95.1%	63.0%
Usenet	31.1%	9.1%	40.1%	4.4	90.9%	59.9%
Weblogs	28.3%	10.9%	39.2%	3.6	89.1%	60.8%
Average	32.6%	10.1%	42.7%	4.5	89.9%	57.3%
	AR & CR					
Newswire	61.2%	16.1%	77.4%	4.8	83.9%	22.6%
Broadcast news	57.8%	17.2%	75.0%	4.4	82.8%	25.0%
Broadcast con.	65.4%	15.2%	80.6%	5.3	84.8%	19.4%
Telephone	84.0%	8.3%	92.3%	11.1	91.7%	7.7%
Usenet	67.0%	13.5%	80.5%	5.9	86.5%	19.5%
Weblogs	58.3%	16.9%	75.1%	4.5	83.1%	24.9%
Average	65.6%	14.5%	80.2%	6.0	85.5%	19.9%

2.7.1.2 Impact of Reference Resolution on Links

Not all entities that are retrieved from some text data as potential nodes for networks will be linked into edges. This can be for two reasons: first, some entities are truly not related to any other entities (isolates), but can be meaningful when they show up in actual network data. About 28% (ACE5) to a third (ACE2) of all entity mentions, and a little over half of the unique entities

(ACE2 and ACE5) do occur in relations. Since over 70% of all entities mentions are impacted by RR, it is seems highly likely that some of the entities occurring in edges can be affected by RR. Second, in most ground truth data for REX, relations are mainly annotated within sentences; disregarding links across sentences or documents. Besides the previously mentioned sparseness that has been observed for many real-world networks, these two reasons also contribute to the sparseness of relational data available for studying REX. Consequently, the density of the relational data used herein, which is computed as the number of actual relations over the number of possible relations, is very low across all genres (Table 16, Table 17) (Wasserman & Faust, 1994).

The ratio of relations that contain at least one node that is a pronoun is very similar across genres in ACE 2 (average of 16%, Table 16), and varies widely in ACE5 (12% to 70%, Table 17). Let's first assume that AR on the link level is only successful if all pronominal nodes in a link can be resolved by a name or nominal. This conservative operationalization is referred to as "AR strict" in the following tables, and allows for determining the minimum amount of change that AR can cause on the link level. Using this approach, the AR rate is high and highly similar across genres; about 75%-78% for spoken data and 79% to 85% for written data. Since the rate of links involving pronouns varies per genre, the ratio of links that are altered due to AR ranges from 9% to 52% (Table 16, Table 17). Relaxing the strict operationalization of successful AR on the link level to assuming that AR is successful if at least one pronoun in a link is resolvable marginally increases the AR rate by an average of 0.6% (Table 17: AR relaxed, this additional analysis conducted for ACE5 only). This additional gain is small for the following reason: in addition to the links impacted by the strict operationalization, the relaxed version also affects links in which both nodes are a pronoun. This applies to 6.3% of all links that have a pronoun, and more than half of them were already completely resolved under the strict AR condition. All nodes on which AR was successful become additional candidates for CR.

Per genre, the number of links between only names and nominals (candidates for CR) is very similar in ACE 2 (83% to 85%, Table 16), and again varies strongly in ACE5 (29% to 82%, Table 17) [4]. The ratio of links that gets reduced when multiple links are mapped onto one link is similar across genres; ranging from 6% to 12%.

As previously explained, CR can also be applied to anaphora[5]. I have operationalized CR on anaphora for the link level as follows: CR on anaphora is successful if both entity mentions in a

[4] For ACE5, the ratio of links with pronouns and links with names and nominals does not add up to 100% due to the inclusion of entities of type timex in links. These entities are not names, nominals or pronouns.

5 In ACE2, there were only three links for which CR was possible on pronouns. Since these effects are marginal I disregard them from analysis on the relation data level.

link are pronouns, and both pronouns map to the same entities as the entity mentions in another link, which are also anaphora. This effect is much smaller than regular CR on the link level (on average 0.3%, Table 17), and smaller than CR on pronouns on the entity level.

Combining AR and CR has a stronger impact on consolidation edges than using either technique alone (last row in Table 16, Table 17): on average, an additional 3% to 4% of all links are reduced. This rate is even higher for telephone and usenet data (not included in average reported in previous sentence), where it exceeds the reduction rate achieved with only performing CR, and adds up to a reduction of 18% to 19% of all links. While the relation reduction is entirely due to CR, AR provides a large amount of names and nominals available to CR.

Table 16: Results for impact of AR and CR on relational data (ACE2)

RR technique applied	Measure of impact of RR on data	Newswire	Newspaper	Broadcast
none	Number of links	2,884	2,956	2,267
	Number of entity mentions	13,356	13,914	12,694
	Density	0.0032	0.0031	0.0028
AR strict	Links with pronoun	14.8%	16.7%	16.5%
	…, pronoun resolved	76.6%	87.0%	76.1%
	…, resolved in corpus	11.3%	14.5%	12.5%
CR	Links with names and nominals	85.2%	83.3%	83.5%
	…, reduced via CR	4.2%	4.7%	7.5%
AR + CR	Links reduced in corpus	6.5%	7.9%	10.6%

Table 17: Results for impact of AR and CR on relational data (ACE5)

RR technique applied	Measure of impact of RR on data	News-wire	Broadc. news	Broadc. conv.	Tele-phone	Usenet	Web-logs
none	Number of links	2,683	2,016	1,660	746	864	769
	Number of entity mentions	11,025	11,461	9,342	9,933	6,516	6,547
	Density	0.0044	0.0031	0.0038	0.0015	0.0041	0.0036
AR strict	Links with pronoun corpus	11.9%	29.6%	25.7%	69.6%	49.4%	26.9%
	…, pronoun resolved	79.6%	78.4%	76.6%	75.0%	78.9%	84.1%
	…, resolved in corpus	9.4%	23.2%	19.7%	52.1%	39.0%	22.6%
	…, unresolved in corpus	2.4%	6.4%	6.0%	17.4%	10.4%	4.3%
relaxed	…, pronoun resolved	80.8%	80.2%	79.4%	76.9%	80.3%	85.0%
	…, resolved in corpus	9.6%	23.7%	20.4%	53.5%	39.7%	22.9%
	…, unresolved in corpus	2.3%	5.9%	5.3%	16.1%	9.7%	4.0%
CR	Links /w name & nomin.	82.0%	65.2%	71.6%	29.1%	49.0%	70.1%
	…, no CR possible	90.0%	93.6%	88.5%	92.6%	88.7%	93.5%
	…, no CR possible in corpus	73.9%	61.0%	63.3%	26.9%	43.4%	65.5%
	…, reduced via CR	10.0%	6.4%	11.5%	7.4%	11.3%	6.5%

	…, reduced via CR in corpus	8.2%	4.2%	8.3%	2.1%	5.6%	4.6%
	…, reduced via CR on anaphora in corpus	0.0%	0.4%	0.4%	0.5%	0.3%	0.0%
	…, sum reduced in corpus	8.2%	4.6%	8.6%	2.7%	5.9%	4.6%
AR + CR	Links reduced in corpus	10.9%	9.7%	13.4%	19.0%	18.4%	8.6%

Overall, the link normalization and deduplication effects due to RR are less strong on the link level than on the entity level (Table 18: values averaged over genres, Table 19). For example, on the entity level, the average weight of unique entities impacted by both, AR and CR, increases from 1.0 to 5.5, while on the link level, the average weight of impacted unique relations increases to less than 2.3. Moreover, the results indicate that on the entity level, CR has a stronger impact (average entity reduction rate = 45.0%) than AR (average entity change rate = 30.8%) does. In contrast to that, on the link level, AR (average link change rate = 22.7) is more effective than CR (average link reduction rate = 5.7%).

Table 18: Comparison of impact of reference resolution techniques on link level, averaged over genres (ACE2)

Case	Impact on data					
	Link change rate (AR), link reduction rate (CR, AR & CR)	Entities impacted by routine			Entities not impacted by routine (node weight = 1)	
		Amount	Total node weight carried	Average node weight	Amount	Total node weight carried
AR	12.8%	12.8%	12.8%	1.00	87.2%	87.2%
CR	5.33%	4.9%	10.0%	2.15	95.1%	90.0%
AR and CR	8.17%	17.4%	24.2%	2.25	82.6%	75.8%

Table 19: Comparison of impact of reference resolution techniques on link level (ACE5)

	Link change rate (AR) and link reduction rate (CR, AR & CR)	Entities impacted by routine			Entities not impacted by routine (node weight = 1)	
		Amount	Total node weight carried	Average node weight	Amount	Total node weight carried
Genre	**AR (relaxed definition)**					
Newswire	9.6%	9.6%	9.6%	1	90.4%	90.4%
Broadcast n.	23.7%	23.7%	23.7%	1	76.3%	76.3%
Broadcast	20.4%	20.4%	20.4%	1	79.6%	79.6%
Telephone	53.5%	53.5%	53.5%	1	46.5%	46.5%
Usenet	39.7%	39.7%	39.7%	1	60.3%	60.3%
Weblogs	22.9%	22.9%	22.9%	1	77.1%	77.1%
Average	28.3%	28.3%	28.3%	1	71.7%	71.7%
	CR (Names and Nominals)					
Newswire	8.2%	7.5%	17.4%	2.33	92.5%	82.6%
Broadcast n.	4.2%	5.8%	12.2%	2.11	94.2%	87.8%
Broadcast	8.3%	9.2%	20.7%	2.26	90.8%	79.3%

Telephone	2.1%	6.9%	14.3%	2.07	93.1%	85.7%
Usenet	5.6%	7.8%	19.1%	2.45	92.2%	80.9%
Weblogs	4.6%	4.6%	11.1%	2.40	95.4%	88.9%
Average	5.5%	7.0%	15.8%	2.27	93.0%	84.2%
	AR + CR (incl. CR on anaphora)					
Newswire	10.9%	8.0%	18.9%	2.36	92.0%	81.1%
Broadcast n.	9.7%	7.8%	17.5%	2.24	92.2%	82.5%
Broadcast	13.4%	10.3%	23.7%	2.30	89.7%	76.3%
Telephone	19.0%	14.3%	33.4%	2.33	85.7%	66.6%
Usenet	18.4%	10.3%	28.7%	2.79	89.7%	71.3%
Weblogs	8.6%	6.0%	14.6%	2.44	94.0%	85.4%
Average	13.3%	9.5%	22.8%	2.41	90.6%	77.2%

2.7.1.3 Impact of Reference Resolution on Network data and Network Data Analysis

In the ground truth data used for this project, the information about entities and relations is provided as unambiguous, numerical identifiers in XML files. This situation is representative for working with social network data where each truly distinct node has a unique key identifier, even if the identifier is anonymized. Such data are typically obtained when collecting network data via surveys and participating observations. However, for semantic network data, unique node identifiers are often not available. In these situations, node names are often used as identifiers. As a consequence, nodes matching in spelling are considered as identical nodes. For practical applications this means that when the network analysis tool encounters a node with the exact same spelling as a previously registered node, the software does not add another node to its data registry, but increases the weight of the previously found node accordingly. This is common procedure in many SNA tools and libraries. For example, when extracting network data with AutoMap, nodes are aggregated based on their spelling and regardless of capitalization, and we have used this approach in a prior study on the impact of reference resolution on network data (J. Diesner & K. M. Carley, 2009). This approach returns correct results if all instances of a person are consistently referred to be the same name, and this name does not coincide with the name of a different person or entity. Problems occur in the cases of homographs and heteronyms (same spelling, different meaning), which cannot be disambiguated based on orthography. For example, if the term “she” is found in multiple files and cannot be resolved or disambiguated, all instances of this node are collected in one node labeled “she”. For this project, I deviate from this common procedure in order to isolate the impact of RR on network data analysis while excluding the impact of coincidentally matching spellings of actually distinct nodes. This strict definition of node uniqueness is realized by using the entity mention IDs provided in ACE as node identifiers, and the heads of these entities as node names. However, I am also providing an empirical

comparison of both approaches to identifying unique nodes (node identity based on ID versus spelling) in order to show the magnitude of the difference (Table 26).

In order to analyze the impact of AR and CR on networks, I created one network per genre and one for the entire corpus after applying each and both reference resolution techniques for the ACE5 data only. The networks are directed, weighted graphs. I used the ORA software to compute a selected set of frequently used network analysis measures on these data. These metrics are defined in Table 153. Since some of these metrics are only defined for symmetric and binary graphs, ORA internally converts the input networks accordingly.

Network analysis is particularly sensitive to the connectivity and weight of nodes and links. These two characteristics impact a node's prominence and importance in the graph, and also the overall network structure. In the analysis on the link level, nodes were only embedded in dyads (regular links), whereas on the network level, a node can be linked to multiple other unique nodes, and the node degree (number of direct links) will increase accordingly. For the analysis on the entity and link level, the impact of heavy "outliers" (hubs) can be diluted by computing average, while on the network level, nodes with a high degree have a strong impact on the overall network (Barabási & Albert, 1999).

Table 20 to Table 26 show the network analysis results in dependence of the RR techniques. The last three columns in each of these tables show the change from the raw data to AR, CR, and AR plus CR. For resolving anaphora on the network level, I used the full set of entities treated with AR techniques. Therefore, it is possible that pronouns get resolved by nodes that were not yet present in the network such that the number of unique nodes in the network can increase from the raw data to data after AR. The following trends are observed for all genres and also the full network: the number of nodes, links and strong and weak components decreases when applying each and both RR routines. Using the RR techniques leads to increases in density, degree centralization, connectedness, transitivity, global efficiency, clustering coefficients, average distance and diffusion. All of these increases and decrease are stronger after applying CR than after using AR (the opposite is true only for telephone data), and also stronger for using AR plus CR than for using CR only. Efficiency and fragmentation are only marginally impacted, and only if AR and CR are both applied. The outcomes for network levels, eigenvector centralization and average speed show changes, but no clear trends.

The betweenness centralization of all networks was zero, which I assume to be due to the sparseness of the data. This assumption is supported by the fact that density values are consistently low. Also, closeness centralization was zero except for one case. The network diameter equaled the number of nodes in all cases. Therefore, the three abovementioned network

centralization measures as well as the diameter are not presented in the results. The eigenvector centralization could not be computed on some of these networks in ORA, and is not reported if not available.

Table 20: Impact of reference resolution techniques on network properties, newswire data

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Link Count	2,669	2,667	2,451	2,390	0%	-8%	-10%
Node Count	4,596	4,447	2,994	2,770	-3%	-35%	-40%
Component Count Strong	4,596	4,447	2,986	2,760	-3%	-35%	-40%
Component Count Weak	1,937	1,795	638	512	-7%	-67%	-74%
Network Levels	4	5	6	6	25%	50%	50%
Density	0.0001	0.0001	0.0003	0.0003	0%	200%	200%
Network Centr. Degree	0.0001	0.0003	0.0009	0.0031	200%	800%	3000%
Network Centr. Eigenvector	1.00	1.00	0.89	0.80	0%	-11%	-20%
Density Clustering Coeff.	0.001	0.002	0.005	0.011	64%	391%	918%
Average Distance	1.13	1.14	1.62	1.66	1%	44%	47%
Average Speed	0.89	0.88	0.62	0.60	-1%	-30%	-32%
Transitivity	0.02	0.02	0.02	0.04	45%	24%	146%
Diffusion	0.0001	0.0002	0.0005	0.0006	100%	400%	500%
Fragmentation	1.000	1.000	0.995	0.994	0%	0%	-1%
Connectedness	0.000	0.000	0.005	0.006	0%	1075%	1450%
Efficiency Global	0.0003	0.0003	0.0018	0.0023	0%	500%	667%
Efficiency	0.991	0.991	0.995	0.994	0%	0%	0%
Hierarchy	1.000	1.000	0.997	0.996	0%	0%	0%
Upper Boundedness	0.69	0.67	0.18	0.20	-3%	-74%	-72%
Interdependence	0	0.0001	0.0002	0.0002	-	-	-

Table 21: Impact of reference resolution techniques on network properties, broadcast news data

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Link Count	2,008	1,999	1,925	1,821	0%	-4%	-9%
Node Count	3,576	3,285	2,920	2,519	-8%	-18%	-30%
Component Count Strong	3,576	3,283	2,920	2,519	-8%	-18%	-30%
Component Count Weak	1,572	1,295	1,015	753	-18%	-35%	-52%
Network Levels	4	5	4	4	25%	0%	0%
Density	0.0002	0.0002	0.0002	0.0003	0%	0%	50%
Network Centr. Degree	0.0003	0.0006	0.0007	0.0021	100%	133%	600%
Network Centr. Eigenvector	0.97	0.96	0.98	0.74	-2%	1%	-24%
Density Clustering Coeff.	0.000	0.001	0.002	0.010	-	-	-
Average Distance	1.10	1.16	1.24	1.26	5%	12%	15%
Average Speed	0.91	0.86	0.81	0.79	-5%	-11%	-13%
Transitivity	0.00	0.01	0.02	0.08	-	-	-
Diffusion	0.0002	0.0002	0.0003	0.0004	0%	50%	100%
Fragmentation	1.000	0.999	0.999	0.998	0%	0%	0%

Connectedness	0.000	0.001	0.001	0.002	50%	175%	300%
Efficiency Global	0.0004	0.0005	0.0007	0.001	25%	75%	150%
Efficiency	0.993	0.995	0.993	0.984	0%	0%	-1%
Hierarchy	1.000	0.999	1.000	1.000	0%	0%	0%
Upper Boundedness	0.73	0.76	0.37	0.47	4%	-50%	-35%
Interdependence	0.0001	0.0001	0.0002	0.0002	0%	100%	100%

Table 22: Impact of reference resolution techniques on network properties, broadcast conversations data

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Link Count	1,656	1,650	1,520	1,438	0%	-8%	-13%
Node Count	2,872	2,648	2,077	1,776	-8%	-28%	-38%
Component Count Strong	2,871	2,646	2,075	1,774	-8%	-28%	-38%
Component Count Weak	1,220	1,006	589	404	-18%	-52%	-67%
Network Levels	4	4	5	5	0%	25%	25%
Density	0.0002	0.0002	0.0004	0.0005	0%	100%	150%
Network Centr. Degree	0.0002	0.0006	0.001	0.0032	200%	400%	1500%
Network Centr. Eigenvector	0.97	0.96	0.76	0.92	-1%	-21%	-4%
Density Clustering Coeff.	0.000	0.001	0.003	0.011	100%	750%	2725%
Average Distance	1.11	1.15	1.34	1.36	4%	21%	23%
Average Speed	0.90	0.87	0.75	0.73	-4%	-17%	-19%
Transitivity	0.01	0.01	0.02	0.06	46%	266%	852%
Diffusion	0.0002	0.0003	0.0005	0.0006	50%	150%	200%
Fragmentation	1.000	0.999	0.997	0.994	0%	0%	-1%
Connectedness	0.001	0.001	0.004	0.006	80%	600%	1060%
Efficiency Global	0.0005	0.0006	0.0016	0.0024	20%	220%	380%
Efficiency	0.995	0.996	0.995	0.992	0%	0%	0%
Hierarchy	1.000	0.999	0.999	0.999	0%	0%	0%
Upper Boundedness	0.76	0.69	0.20	0.22	-9%	-74%	-72%
Interdependence	0.0001	0.0001	0.0003	0.0003	0%	200%	200%

Table 23: Impact of reference resolution techniques on network properties, telephone conversations data

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Link Count	746	739	730	604	-1%	-2%	-19%
Node Count	1,377	1,079	1,161	799	-22%	-16%	-42%
Component Count Strong	1,377	1,077	1,161	797	-22%	-16%	-42%
Component Count Weak	631	347	435	212	-45%	-31%	-66%
Network Levels	4	4	4	4	0%	0%	0%
Density	0.0004	0.0006	0.0005	0.0009	50%	25%	125%
Network Centr. Degree	0.0011	0.0048	0.002	0.0072	336%	82%	555%
Network Centr. Eigenvector	0.9993	0.9813	0.7053	0.9562	-2%	-29%	-4%
Density Clustering Coeff.	0.000	0.003	0.000	0.009	-	-	-
Average Distance	1.08	1.24	1.13	1.27	15%	5%	17%
Average Speed	0.93	0.80	0.88	0.79	-13%	-5%	-15%

Transitivity	0.00	0.02	0.00	0.07	-	-	-
Diffusion	0.0004	0.0008	0.0006	0.0012	100%	50%	200%
Fragmentation	0.999	0.995	0.998	0.992	0%	0%	-1%
Connectedness	0.001	0.005	0.002	0.008	456%	122%	778%
Efficiency Global	0.0009	0.0027	0.0015	0.0041	200%	67%	356%
Efficiency	1.000	0.997	0.994	0.991	0%	-1%	-1%
Hierarchy	1.000	0.997	1.000	0.996	0%	0%	0%
Upper Boundedness	0.76	0.76	0.30	0.54	0%	-60%	-29%
Interdependence	0.0001	0.0002	0.0005	0.0005	100%	400%	400%

Table 24: Impact of reference resolution techniques on network properties, usenet data

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Link Count	858	846	811	705	-1%	-5%	-18%
Node Count	1,547	1,322	1,208	936	-15%	-22%	-39%
Component Count Strong	1,547	1,322	1,208	936	-15%	-22%	-39%
Component Count Weak	692	479	402	247	-31%	-42%	-64%
Network Levels	3	6	4	4	100%	33%	33%
Density	0.0004	0.0005	0.0006	0.0008	25%	50%	100%
Network Centr. Degree	0.0008	0.0016	0.0022	0.0067	100%	175%	738%
Network Centr. Eigenvector	1.00	0.98	0.99	0.98	-2%	-1%	-2%
Density Clustering Coeff.	0.002	0.002	0.003	0.011	0%	53%	453%
Average Distance	1.08	1.25	1.24	1.33	16%	16%	24%
Average Speed	0.93	0.80	0.80	0.75	-14%	-14%	-19%
Transitivity	0.03	0.01	0.02	0.05	-62%	-38%	38%
Diffusion	0.0004	0.0006	0.0007	0.0011	50%	75%	175%
Fragmentation	0.999	0.997	0.997	0.993	0%	0%	-1%
Connectedness	0.001	0.003	0.003	0.007	211%	222%	667%
Efficiency Global	0.0008	0.0017	0.0018	0.0036	113%	125%	350%
Efficiency	0.985	0.998	0.996	0.993	1%	1%	1%
Hierarchy	1.000	1.000	1.000	1.000	0%	0%	0%
Upper Boundedness	0.68	0.85	0.29	0.47	25%	-57%	-31%
Interdependence	0.0001	0.0002	0.0005	0.0005	100%	400%	400%

Table 25: Impact of reference resolution techniques on network properties, blog data

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Link Count	766	766	732	703	0%	-4%	-8%
Node Count	1,407	1,331	1,137	1,031	-5%	-19%	-27%
Component Count Strong	1,407	1,331	1,137	1,031	-5%	-19%	-27%
Component Count Weak	643	567	412	340	-12%	-36%	-47%
Network Levels	3	4	4	4	33%	33%	33%
Density	0.0004	0.0004	0.0006	0.0007	0%	50%	75%
Network Centr. Degree	0.0003	0.0009	0.0015	0.0052	200%	400%	1633%

Network Centr. Eigenvector	0.79	0.98	0.94	0.95	25%	20%	21%
Density Clustering Coeff.	0.001	0.001	0.004	0.009	0%	236%	755%
Average Distance	1.06	1.10	1.20	1.24	4%	13%	17%
Average Speed	0.94	0.91	0.83	0.80	-4%	-12%	-15%
Transitivity	0.02	0.02	0.03	0.06	-35%	19%	144%
Diffusion	0.0004	0.0005	0.0007	0.0008	25%	75%	100%
Fragmentation	0.999	0.999	0.997	0.997	0%	0%	0%
Connectedness	0.001	0.001	0.003	0.003	44%	200%	278%
Efficiency Global	0.0008	0.001	0.0017	0.0022	25%	113%	175%
Efficiency	0.987	0.994	0.993	0.989	1%	1%	0%
Hierarchy	1.000	1.000	1.000	1.000	0%	0%	0%
Upper Boundedness	0.71	0.78	0.37	0.50	10%	-47%	-30%
Interdependence	0.0001	0.0001	0.0005	0.0005	0%	400%	400%

The results from disambiguating and consolidating nodes based on node IDs versus node spelling differ strongly (Table 26). With the spelling based approach, for 2/3 of the considered measures, AR and CR exhibit opposite effects with respect to increasing or decreasing the value of a measure, AR causes a greater change than CR, and the joint impact of AR and CR is moderate in most cases (for 13 of 20 measures, the combined change rate is 10% and less). These effects are consistent with our previous findings (J. Diesner & K. M. Carley, 2009), but differ starkly from the ID based approach. There, AR and CR both either increase or decrease a metric (except for upper boundedness), CR has a stronger impact than AR does, and the joint impact of AR and CR is much larger (7 out of 20 measures have a change rate of 10% and less). In summary, the results for node disambiguation approaches suggest that consolidating nodes based on their spelling leads to network data, analysis results and interpretations that strongly deviate from what is suggested by the ground truth, and allows for a smaller overall effect of applying RR.

Table 26: Impact of reference resolution techniques on network properties, node identity based on spelling versus node ID, all genres

Measure	Raw	AR	CR	AR & CR	Raw to AR	Raw to CR	Raw to AR & CR
Entire network, node disambiguation and consolidation based on node ID							
Link Count	8,703	8,667	8,169	7,661	0%	-6%	-12%
Count Node	15,375	14,112	11,497	9,831	-8%	-25%	-36%
Component Count Strong	15,374	14,106	11,487	9,817	-8%	-25%	-36%
Component Count Weak	6,695	5,489	3,491	2,468	-18%	-48%	-63%
Network Levels	4	6	6	6	50%	50%	50%
Density	0	0	0.0001	0.0001	-	-	-
Network Centr. Degree	0.0001	0.0001	0.0002	0.0009	0%	100%	800%
Network Centr., Between.	0	0	0	0	-	-	-
Density Clustering Coeff.	0.001	0.001	0.003	0.011	100%	357%	1400%

Average Distance	1.10	1.16	1.39	1.44	6%	26%	30%
Speed Average	0.91	0.86	0.72	0.70	-5%	-21%	-23%
Transitivity	0.01	0.02	0.02	0.05	41%	81%	370%
Diffusion	0	0.0001	0.0001	0.0001	-	-	-
Fragmentation	1.00	1.00	1.00	1.00	0%	0%	0%
Connectedness	0.0001	0.0002	0.0006	0.0009	100%	500%	800%
Efficiency Global	0.0001	0.0001	0.0003	0.0004	0%	200%	300%
Efficiency	0.992	0.995	0.995	0.992	0%	0%	0%
Hierarchy	1.000	0.999	0.998	0.998	0%	0%	0%
Upper Boundedness	0.72	0.75	0.22	0.27	4%	-70%	-63%
Interdependence	0	0	0.0001	0.0001	-	-	-
Entire network, node disambiguation and consolidation based on node spelling							
Link Count	6,475	6,669	6,561	6,514	3%	1%	1%
Count Node	3,299	3,518	3,215	3,323	7%	-3%	1%
Component Count Strong	2,780	2,988	2,638	2,763	7%	-5%	-1%
Component Count Weak	165	170	124	130	3%	-25%	-21%
Network Levels	21	21	20	23	0%	-5%	10%
Density	0.0006	0.0005	0.0006	0.0006	-17%	0%	0%
Network Centr. Degree	0.0009	0.0008	0.0011	0.0008	-11%	22%	-11%
Network Centr., Between.	0.029	0.038	0.033	0.037	33%	14%	30%
Density Clustering Coeff.	0.013	0.019	0.028	0.045	47%	110%	240%
Average Distance	5.69	6.31	5.80	6.47	11%	2%	14%
Speed Average	0.18	0.16	0.17	0.15	-10%	-2%	-12%
Transitivity	0.04	0.04	0.05	0.04	-9%	8%	3%
Diffusion	0.1891	0.1719	0.2160	0.1905	-9%	14%	1%
Fragmentation	0.21	0.21	0.16	0.17	0%	-22%	-20%
Connectedness	0.7931	0.7926	0.8391	0.8342	0%	6%	5%
Efficiency Global	0.1873	0.1757	0.1993	0.1833	-6%	6%	-2%
Efficiency	0.999	0.999	0.999	0.999	0%	0%	0%
Hierarchy	0.931	0.930	0.919	0.921	0%	-1%	-1%
Upper Boundedness	0.64	0.58	0.67	0.60	-10%	5%	-6%
Interdependence	0.0001	0.0001	0.0001	0.0001	0%	0%	0%

For practical applications on network analysis, people are often also interested in identifying the set of nodes that score highest on a certain measure or a set of measures. This procedure is also called "key player analysis". I perform a key player analysis on the data by using ORA to compute several network analytical measures for every node per network, and comparing the top five ranking nodes after each RR technique was applied (Table 27, tying nodes are listed in alphabetical order). These qualitative findings complement the quantitative results that were reported up to here.

For resolution based on node IDs, the results show that the set of key entities identified when not applying any RR technique are completely different from the key entities found after applying RR. When performing both, AR and CR, the key entities for betweennees centrality and in-

degree centrality are similar to the key entities found after using CR only, and the key players with respect to inverse closeness centrality and out-degree centrality resemble those identified by using AR only. Since the values per measure and node are overall higher and more often different from zero for betweennees centrality and in-degree centrality than for inverse closeness centrality and out-degree centrality, the findings for similarities between CR and AR plus CR are more robust than the similarities after using AR. For practical applications, this means that performing at least CR will cause a major change in the network data, which resembles the ground truth more closely than using no RR or AR only.

Several two top scoring nodes in the raw data are pronouns, e.g. which, she, all, and they, which are unlikely to present the actual agents who drive the dynamics of a system. Ironically, the top scoring node w.r.t. out-degree centrality is “we”. What looks like a mistake represents the fact that especially in the accounts of spoken language as well as in the social media data data, “we” is a frequently occurring entity that sometimes cannot be resolved via AR, but consolidated via CR.

Another relevant finding here is that when consolidating nodes based on their spelling, the set of key players identified with and without using any RR techniques are highly similar to each other. Interpreting this finding together with the outcome of the quantitative network analysis suggests the when normalizing nodes based on spelling, RR makes a much smaller difference with respect to changes in network analytical measures and identified key players than when normalizing nodes based on actual node IDs. Taking this interpretation a step further implies that if only key players and a certain set of measures (listed at end of the sentence) are computed, conducting any RR technique is not worthwhile if nodes are normalized based on spelling (number of nodes, number of links, strong components, network levels, density, transitivity, diffusion, connectedness, global efficiency, efficiency, hierarchy, upper boundedness, interdependence). However, the results obtained that way do not resemble the ground truth.

Table 27: Key entities, node identity based on spelling versus node ID, all genres, ACE5

	Node disambiguation and consolidation based on node ID				**Node disambiguation and consolidation based on node spelling**			
Rank	Betwee-nness centrality	Inverse closeness centrality	In-degree centrality	Out-degree centrality	Between-ness centrality	Inverse closeness centrality	In-degree centrality	Out-degree centrality
	Raw							
1	home	soldiers	Washington	all	Iraq	director	U.S	his
2	Byrds Creek	she	area	ambassadors	I	founder	Iraqi	forces
3	base	boy	home	Protesters	they	chairman	Iraq	troops
4	streets	forces	which	diplomats	his	Chiefs of Staff	Baghdad	my
5	mosque	forces	Tuesday	Iraqis	area	Giuliani	there	I
	AR							

1	Judy	parents	company	Judy	Iraq	Roger	U.S	forces
2	Ringo Langly	Judy	headquarters	GF	troops	guy	Iraqi	troops
3	GF	Annie J.S.	base	dogbirdh@...	forces	executive	Iraq	people
4	kramer	guy	group	Britt	family	director	Baghdad	officials
5	dad	Britt	US	Annie J.S.	people	chairman	city	President
	CR							
1	Indonesia	forces	country	Stig Toefting	his	director	U.S	his
2	Iraq	Buildings	Palestinian	terrorist	people	Council	Iraq	forces
3	Iraqi	source	Iraqi	bomber	Iraq	head	Iraqi	troops
4	city	TV2	American	Iraq	I	Protesters	Baghdad	my
5	Stig Toefting	Copenhagen	Indonesia	troops	Baghdad	Task Force	country	I
	AR & CR							
1	Indonesia	parents	country	we	Iraq	Council	U.S	troops
2	Iraqi	Judy	Palestinian	private	people	head	Iraq	forces
3	Iraqi	mother	Indonesia	Marwan B.	President	Shaq	Iraqi	people
4	Stig Toefting	Mildred	Iraqi	Judy	U.S	Copenhagen	Baghdad	officials
5	city	industry	U.S	GF	troops	TV2	country	President

2.7.1.4 Simulation of impact of reference resolution error rates

The last research question for the RR project is about the impact of changes in the accuracy of AR and CR on the network data. I use the following procedure in order to study the effect of introducing typical RR errors into ground truth data: My review of typical error rates achieved with current, publically available and top performing RR tools has shown that precision is about ten percent higher than recall, and that recall and precision range between 55% to 85%, and 65% to 95%, respectively (Table 4). Based on this review of empirical results, I defined the following four settings for accuracy rates as shown in Table 28 for experimentation. Next, I assume that the ground truth data are the gold standard against which the performance of a reference resolution tool would be compared in order to assess its accuracy. This procedure resembles the way accuracy assessment is actually done in NLP. Based on this assumption, I introduce errors into the ground truth data such that the resulting data have the error rates specified in Table 28 as follows: I generate false negatives by removing randomly selected links from the ground truth until a given recall rate has been reached. Once this is done, I add false positives into the data by connecting nodes that are not linked in the ground truth, but are defined as valid nodes in the ground truth. The weight of added links is selected proportionally to the distribution of link weights in the ground truth, which differs per RR technique and was treated that way. Once the data with the given error rates have been constructed, I perform the same network analysis on them as presented in the previous section in order to allow for comparability of the findings. These analyses were performed for the ACE5 data on the entire corpus level.

Table 28: Accuracy rates for reference resolution for experiments

	Precision	Recall	F
Accuracy I	55	65	60
Accuracy II	65	75	70
Accuracy III	75	85	80
Accuracy VI	85	95	90

Table 29 to Table 31 show the network analytical measure in dependence of an increase in accuracy by 10% for the first four columns, and the difference between the values computed on the ground truth data to each accuracy setting in the last four columns. The following trends can be observed for all of AR, CR and AR plus CR: The most common effect is that increases in accuracy lead to decreases in the underestimation of the following metrics (listed by decreasing amount of underestimating): upper boundedness, transitivity, clustering coefficient, the number of strong and weak components, the number of nodes and links, and average speed. For either and both RR techniques, increases in accuracy also lead to decreases in the overestimates of the following metrics (listed by decreasing amount of overestimating): connectedness, diffusion, global efficiency, network levels, and degree centralization. Improving the accuracy for all and both RR techniques has virtually no impact of network density, fragmentation and efficiency.

Overall, even small error rates can cause huge changes in the value of network metrics. To illustrate this effect, I have underlined the conditions under which changes occur and where the difference between the true value and the value obtained using a certain error rate is equal to or less than 10%. This applies only to metrics which did show no clear trend in how they change depending on RR techniques as discussed in section 2.7.1.3, namely efficiency, fragmentation, network levels, and speed, or requires the highest accuracy rate tested to achieve this effect, which applies to diffusion and the number of links only.

Table 29: Change in network properties depending on error rates for AR

Measure	Accu-racy I	Accu-racy II	Accu-racy III	Accu-racy IV	Ground Truth	Acc I to GT	Acc II to GT	Acc III to GT	Acc IV to GT
Connectedness	0.0034	0.0040	0.0005	0.0003	0.0002	1600%	1900%	150%	50%
Efficiency Global	0.0006	0.0005	0.0002	0.0002	0.0001	500%	400%	100%	100%
Diffusion	0.0001	0.0001	0.0001	0.0001	0.0001	<u>0%</u>	<u>0%</u>	<u>0%</u>	<u>0%</u>
Network Levels	10	9	8	6	6	67%	50%	33%	<u>0%</u>
Nw. Centr. Degree	0.0003	0.0002	0.0002	0.0002	0.0001	200%	100%	100%	100%
Upper Boundedness	0.11	0.06	0.44	0.60	0.75	-86%	-92%	-41%	-19%
Transitivity	0.001	0.002	0.003	0.010	0.016	-92%	-89%	-81%	-39%
Average Distance	1.90	1.76	1.52	1.27	1.16	63%	51%	30%	<u>9%</u>
Density Clus. Coeff.	0.0004	0.0005	0.0006	0.0013	0.0014	-71%	-64%	-57%	<u>-7%</u>
Comp. Count Weak	2,613	3,110	3,775	4,654	5,489	-52%	-43%	-31%	-15%
Average Speed	0.53	0.57	0.66	0.78	0.86	-39%	-34%	-23%	<u>-9%</u>
Node Count	9,973	10,642	11,422	12,387	14,112	-29%	-25%	-19%	-12%

Comp. Count Strong	9,971	10,640	11,419	12,383	14,106	-29%	-25%	-19%	-12%
Link Count	7,368	7,539	7,662	7,765	8,667	-15%	-13%	-12%	-10%
Fragmentation	0.997	0.996	1.000	1.000	1.000	0%	0%	0%	0%
Efficiency	1.000	1.000	1.000	0.998	0.995	0%	0%	0%	0%
Hierarchy	1.00	1.00	1.00	1.00	1.00	0%	0%	0%	0%
Density	0.0001	0.0001	0.0001	0.0001	0	-	-	-	-

Table 30: Change in network properties depending on error rates for CR

Measure	Accu-racy I	Accu-racy II	Accu-racy III	Accu-racy IV	Ground Truth	Acc I to GT	Acc II to GT	Acc III to GT	Acc IV to GT
Connectedness	0.2014	0.1277	0.0416	0.0013	0.0006	>33tsd%	>21tsd%	6833%	117%
Efficiency Global	0.0122	0.0075	0.0024	0.0004	0.0003	3967%	2400%	700%	33%
Diffusion	0.0003	0.0002	0.0002	0.0001	0.0001	200%	100%	100%	0%
Network Levels	15	11	11	8	6	150%	83%	83%	33%
Nw. Centr. Degree	0.0003	0.0005	0.0004	0.0003	0.0002	50%	150%	100%	50%
Upper Boundedness	0.00	0.00	0.01	0.13	0.22	-98%	-98%	-96%	-38%
Transitivity	0.001	0.004	0.007	0.012	0.021	-95%	-81%	-68%	-40%
Average Distance	2.99	2.33	2.04	1.56	1.39	115%	68%	47%	12%
Density Clus. Coeff.	0.0004	0.0008	0.0018	0.0020	0.0032	-88%	-75%	-44%	-38%
Comp. Count Weak	1,558	1,914	2,387	2,965	3,491	-55%	-45%	-32%	-15%
Average Speed	0.33	0.43	0.49	0.64	0.72	-54%	-40%	-32%	-11%
Node Count	8,421	8,924	9,556	10,195	11,497	-27%	-22%	-17%	-11%
Comp. Count Strong	8,416	8,922	9,549	10,191	11,487	-27%	-22%	-17%	-11%
Link Count	6,968	7,100	7,236	7,322	8,169	-15%	-13%	-11%	-10%
Fragmentation	0.799	0.872	0.958	0.999	0.999	-20%	-13%	-4%	0%
Efficiency	1.000	1.000	1.000	0.998	0.995	1%	1%	1%	0%
Hierarchy	1.00	1.00	1.00	1.00	1.00	0%	0%	0%	0%
Density	0.0001	0.0001	0.0001	0.0001	0.0001	0%	0%	0%	0%

Table 31: Change in network properties depending on error rates for AR and CR

Measure	Accu-racy I	Accu-racy II	Accu-racy III	Accu-racy IV	Ground Truth	Acc I to GT	Acc II to GT	Acc III to GT	Acc IV to GT
Connectedness	0.3318	0.2704	0.1608	0.0046	0.0009	>36tsd%	29tsd%	>17tsd%	411%
Efficiency Global	0.0225	0.0191	0.0095	0.0008	0.0004	5525%	4675%	2275%	100%
Diffusion	0.0004	0.0004	0.0002	0.0001	0.0001	300%	300%	100%	0%
Network Levels	18	15	16	9	6	200%	150%	167%	50%
Nw. Centr. Degree	0.0012	0.0009	0.001	0.001	0.0009	33%	0%	11%	11%
Upper Boundedness	0.00	0.01	0.00	0.07	0.27	-98%	-98%	-98%	-74%
Transitivity	0.007	0.008	0.018	0.027	0.053	-87%	-85%	-65%	-49%
Average Distance	3.14	3.13	2.37	1.69	1.44	118%	117%	65%	17%
Density Clus. Coeff.	0.0026	0.0027	0.0051	0.0060	0.0105	-75%	-74%	-51%	-43%
Comp. Count Weak	1,088	1,285	1,642	2,114	2,468	-56%	-48%	-33%	-14%
Average Speed	0.32	0.32	0.42	0.59	0.70	-54%	-54%	-39%	-15%
Node Count	7,394	7,785	8,268	8,819	9,831	-25%	-21%	-16%	-10%
Comp. Count Strong	7,394	7,780	8,265	8,812	9,817	-25%	-21%	-16%	-10%
Link Count	6,509	6,723	6,800	6,866	7,661	-15%	-12%	-11%	-10%
Fragmentation	0.668	0.730	0.839	0.995	0.999	-33%	-27%	-16%	0%

Efficiency	1.000	1.000	1.000	0.999	0.992	1%	1%	1%	1%
Hierarchy	1.00	1.00	1.00	1.00	1.00	0%	0%	0%	0%
Density	0.0001	0.0001	0.0001	0.0001	0.0001	0%	0%	0%	0%

In order to test the qualitative impacts of the given error rates, I performed the same type of key player analysis as previously presented in this chapter. The outcomes ((Table 32 to Table 34) differ from what the quantitative analysis had suggested: for both RR techniques individually and combined, there is a large amount of overlap in key entities between the ground truth and key entities found at lower RR accuracy rates, especially with respect to node degree centrality and even for rather low accuracy rates. This finding suggests that the set of key players is less sensitive towards changes in accuracy rates than network analytical measures. Also, the key players are similar for CR and AR plus CR, but rather different set of key players is identified when using AR only. This suggests that AR has a smaller impact on the combined results than CR does.

Table 32: Change in key players depending on error rates for AR

Betweenness centrality	Inverse closeness centrality	In-degree centrality	Out-degree centrality
Accuracy I			
Judy	organization	Judy	Annie Juhlyn Simon
dogbirdh...@yahoo.com	Lynn	company	Judy
base	Jabaliya	streets	dogbirdh...@yahoo.com
Annie Juhlyn Simon	area	U.S	Barbara Sz.
GF	Universal Orlando	headquarters	roommate
Accuracy II			
Ringo Langly	industry	group	dogbirdh...@yahoo.com
roommate	grandmother	BIL	Britt
base	Giuliani	fort hood	GF
nephew	Rudolph Giuliani	Washington DC	Mark
man	companion	headquarters	Judy
Accuracy III			
teacher	possessions	base	Judy
Judy	body	fort hood	GF
Mildred	guy	company	dogbirdh...@yahoo.com
dogbirdh...@yahoo.com	closet	US	Annie Juhlyn Simon
students	parents	group	Britt
Accuracy VI			
Judy	head	headquarters	Judy
teacher	court	company	GF
AIG	parents	group	dogbirdh...@yahoo.com
tracy	Judy	Washington DC	Annie Juhlyn Simon
court	Annie Juhlyn Simon	fort hood	Barbara Sz.
Ground truth			
Judy	parents	company	Judy
Ringo Langly	Judy	headquarters	GF
GF	Annie Juhlyn Simon	base	dogbirdh@ yahoo.com

kramer	guy	group	Britt
dad	Britt	US	Annie Juhlyn Simon

Table 33: Change in key players depending on error rates for CR

Betweenness centrality	Inverse closeness centrality	In-degree centrality	Out-degree centrality
Accuracy I			
Agartala	we	Palestinian	Stig Toefting
son	who	Indonesia	soldiers
Indonesia	forces	people	bomber
people	new york	Israeli	members
members	reserves	US	Vivendi Universal
Accuracy II			
American	troops	country	Giuliani
Iraqi	rats	Palestinian	terrorist
city	Diller	American	you
Iraqi	resistance	Iraqi	McCarthy
Patriot	McCarthy	Indonesia	Iraq
Accuracy III			
Stig Toefting	neighborhood	country	Stig Toefting
Iraq	North Korean	US	members
Israel	Stig Toefting	Palestinian	terrorist
crossing	parliament	American	Iraq
Denmark	ambassador	American	North Korean
Accuracy VI			
American	its	Iraqi	Giuliani
Indonesia	park	American	Iraq
baby	Vivendi Universal	country	Indonesia
Iraqi	officials	people	michael sears
williams	troops	Palestinian	terrorist
Ground truth			
Indonesia	forces	country	Stig Toefting
Iraq	Buildings	Palestinian	terrorist
Iraqi	source	Iraqi	bomber
city	TV2	American	Iraq
Stig Toefting	Copenhagen	Indonesia	troops

Table 34: Change in key players depending on error rates for AR and CR

Betweenness centrality	Inverse closeness centrality	In-degree centrality	Out-degree centrality
Accuracy I			
Iraqi	ambassador	American	private
abby	your	country	girlfriend
house	Karim	American	Britt
Baghdad	minister	people	JBELLU...@COMCAST.
we	woman	Indonesia	people
Accuracy II			
mother	secretary	people	private
Security Council	troops	Iraqi	your

troop	soldiers	American	terrorist
private	state	Israel	Britt
Saudi	U.S	group	Judy
Accuracy III			
Hebron	street	country	we
American	clerics	Palestinian	Stig Toefting
prize	demonstrators	Israeli	private
Northwestern	minority	Indonesia	Britt
workers	area	Israel	terrorist
Accuracy VI			
Britt	boy	country	we
Baghdad	Mildred	US	Mildred
Indonesia	village	Indonesia	Judy
American	industry	Palestinian	Stig Toefting
court	source	American	mother
Ground truth			
Indonesia	parents	country	we
Iraqi	Judy	Palestinian	private
Iraqi	mother	Indonesia	Marwan B.
Stig Toefting	Mildred	Iraqi	Judy
city	industry	U.S	GF

2.7.1.5 Answers to research questions

The presented results for reference resolution on the entity or node level suggest the answers to my research questions presented in Table 35. All numbers reported there are averages..

Table 35: Answers to research questions.

Level of analysis	**How large is the impact of RR techniques?**	**Which routine, AR or CR, is more effective in achieving these effects?**	**Is combining AR and CR more effective than either technique alone?**
1. Entity level	Performing RR alters the identity and/or weight of 76% of all entity mentions. The entity weight is increased from 1.0 to 4.9 with AR, to 4.5 with CR, and to 5.8 with AR and CR. Less than 18% of the unique entities are impacted by RR; they carry more than 79% of the total entity weight.	CR w.r.t. amount of entities changed. AR w.r.t. increasing the weight of impacted entities. The rate of entity reduction via CR is 45%. The rate of entity change via AR is 31%.	Yes. Combining both techniques increases the amount of entities impacted by RR by another 38%.
2. Link level	The link weight is increased from 1.0 to 2.4 by using RR. The weight of unique relations impacted by both techniques increases to less	AR. The link reduction rate due to CR is 6%. The link change rate due	Yes. When applying both techniques, 12% of all links are

	than 2.5. Less than 11% of the unique links are impacted by RR; they carry almost 23% of the total link weight.	to AR is 23%.	reduced. The impact of RR is stronger on the node level than on the link level.
3. Network level	Using RR leads to increases in network density, connectedness, transitivity, degree centralization, global efficiency, clustering coefficients, average distance and diffusion. Disambiguating nodes based on node IDs versus node spelling makes a big difference; using the latter approach leads to analysis results and interpretations that strongly deviate from the ground truth.	CR. When identifying key entities, CR closely resembles the nodes identified by using AR and CR, while applying AR only returns a completely different set of key entities.	Yes.

Question 4: How much change in network properties in due to increases in accuracy of AR and CR?

Answer 4: Even small error rates, e.g. an F value for accuracy of 90%, can cause over- and underestimations of the true network analytical values per metric of much more than 10%; often ranging up to 100% and more. In contrast to that, the identification of key entities is less sensitive towards changes in RR accuracy rates than the network analytical measures are. Also, the set of key entities is strongly impacted by CR, and less so by AR.

2.7.2 Windowing

The operationalization of "window size" for this project is the number of space separated tokens that occur between the heads of the nodes that are involved in any annotated relation. The nodes themselves are not within the window. For example, if two nodes in a relation occur adjacent to each other, the window size is zero. If no head is available for an entity, which applies all instances of the timex" class, the number of tokens between the extents of the nodes is counted. Genitive markers ('s) can be separated by a single space character from the token they belong to. They are disregarded from counting the length of the window. The same applies to hyphens and single-character punctualization symbols, including commas.

The chosen operationalization of windowing slightly differs from another common way of measuring the length of the window, where the linked nodes are within the window. For example, if two adjacent unigrams would form a link, the window size would be two. The latter approach is used in AutoMap (K.M. Carley, Columbus, Bigrigg, & Kunkel, 2011). I chose the

abovementioned operationalization in order to avoid any conflicts with entities that are multi-word expressions so that the results presented herein eliminate this source of ambiguity.

In the context of this project, the SemEval data complement the ACE datasets in several ways: first, in SemEval, different types of semantic relations are considered than in ACE (see Table 36 for a list of the relations in SemEval). These relations are based on prior work in semantic role labeling (Nastase & Szpakowicz, 2003). Second, in SemEval, only relations between nominals, i.e. nouns and base noun phrases, are annotated, but not between named entities or pronouns. Third, the examples in SemEval are limited to statements about real world situations. This means that negations, modalities, and opinions are exluded; all of which are represented in ACE. Fourth, the SemEval data were collected more recently than the ACE data, and are not confined to specific genres or domains. The drawback with this less constrained data collection procedure is that we do not know the production or release date and genre or domain of the selected texts. Finally, in ACE, the types of entities are not annotated. These differences will allow for testing the robustness of window sizes across these different aspects.

Table 36: Types of relationships and size in corpus (SemEval)

Type of Semantic Relationship	Number of Links	Ratio in Corpus
Cause-Effect	1331	12.4%
Component-Whole	1253	11.7%
Content-Container	732	6.8%
Entity-Destination	1137	10.6%
Entity-Origin	974	9.1%
Instrument-Agency	660	6.2%
Member-Collection	923	8.6%
Message-Topic	895	8.4%
Other	1864	17.4%
Product-Producer	948	8.8%

2.7.2.1 Typical window sizes and link coverage rates

The results presented in Table 37 suggest that typical window sizes as well as the ratio of links that are found when using a certain window size (coverage rate) are highly similar across different types of semantic relationships: for all types of relations, more than half of the links are found with a window size of four. On average, a window size of seven is needed to identify more than 90% of the links, and with a window size of eight, over 95% of the links are retrieved. The most frequent window size that humans apply is small, typically two or three (those values underlined in Table 37).

Table 37: Impact of type of semantic relationship on window size (SemEval)

Per Link Type: Ratio of links with this size (left), Cumulative coverage of links at this size (right)

Window Size	Cause Effect		Component Whole		Content Container		Entity Destination		Entity Origin		Instrument Agency	
0	1.4%	1.4%	12.1%	12.1%	1.2%	1.2%	0.0%	0.0%	15.8%	15.8%	4.8%	4.8%
1	11.6%	12.9%	4.5%	16.7%	7.1%	8.3%	3.8%	3.8%	0.8%	16.6%	7.1%	12.0%
2	14.0%	27.0%	40.8%	57.5%	18.7%	27.0%	26.3%	30.1%	13.0%	29.7%	19.2%	31.2%
3	20.7%	47.7%	14.1%	71.6%	32.1%	59.2%	20.4%	50.5%	18.6%	48.3%	14.2%	45.5%
4	15.3%	63.0%	8.1%	79.7%	17.1%	76.2%	22.7%	73.2%	20.4%	68.7%	8.5%	53.9%
5	10.1%	73.0%	6.7%	86.4%	11.2%	87.4%	15.8%	89.0%	13.9%	82.5%	12.0%	65.9%
6	8.9%	82.0%	5.5%	91.9%	6.0%	93.4%	5.9%	94.9%	8.4%	91.0%	10.9%	76.8%
7	7.0%	89.0%	3.3%	95.2%	1.9%	95.4%	1.8%	96.7%	3.7%	94.7%	7.3%	84.1%
8	3.5%	92.4%	1.5%	96.7%	1.9%	97.3%	1.2%	98.0%	2.2%	96.8%	4.7%	88.8%
9	2.6%	95.0%	0.9%	97.6%	1.0%	98.2%	0.6%	98.6%	1.4%	98.3%	3.2%	92.0%
10	1.6%	96.5%	1.2%	98.8%	0.1%	98.4%	0.8%	99.4%	0.4%	98.7%	2.4%	94.4%
11	0.9%	97.4%	0.6%	99.4%	0.7%	99.0%	0.4%	99.7%	0.5%	99.2%	1.8%	96.2%
12	1.1%	98.6%	0.1%	99.5%	0.1%	99.2%	0.2%	99.9%	0.1%	99.3%	1.1%	97.3%

Window Size	Member Collection		Message Topic		Product Producer		Other		Average (unweighted)	
0	2.2%	2.2%	0.7%	0.7%	12.6%	12.6%	6.8%	6.8%	5.8%	5.8%
1	37.7%	39.9%	5.9%	6.6%	6.1%	18.7%	9.2%	16.0%	9.4%	15.1%
2	42.7%	82.6%	22.9%	29.5%	14.9%	33.5%	21.5%	37.4%	23.4%	38.6%
3	9.8%	92.3%	19.2%	48.7%	22.2%	55.7%	20.1%	57.5%	19.1%	57.7%
4	3.3%	95.6%	16.1%	64.8%	16.5%	72.2%	15.0%	72.5%	14.3%	72.0%
5	2.6%	98.2%	12.1%	76.9%	8.2%	80.4%	10.4%	82.8%	10.3%	82.3%
6	0.8%	98.9%	7.7%	84.6%	6.1%	86.5%	6.5%	89.3%	6.7%	88.9%
7	0.5%	99.5%	6.6%	91.2%	4.4%	90.9%	3.9%	93.2%	4.0%	93.0%
8	0.3%	99.8%	3.1%	94.3%	2.1%	93.0%	2.1%	95.4%	2.3%	95.3%
9	0.1%	99.9%	2.2%	96.5%	1.9%	94.9%	2.0%	97.4%	1.6%	96.8%
10	0.0%	99.9%	1.3%	97.9%	1.3%	96.2%	0.8%	98.2%	1.0%	97.8%
11	0.0%	99.9%	1.0%	98.9%	0.8%	97.0%	0.7%	98.9%	0.7%	98.6%
12	0.0%	99.9%	0.6%	99.4%	0.9%	98.0%	0.4%	99.3%	0.5%	99.0%

There are a few noteworthy differences depending on the type of semantic relationships: for "member - collection" links, which encode non-functional relationships between specific elements and some set, the window is particularly short: over 80% of nodes in a link are separated by one or two words in the text. In contrast to that, two types of relations require a slighty larger window than the reported averages (greater by one to two words): first, "instrument - agency" relations, which denote than somebody or something uses some object, and second "cause - effect" relations, which represent the fact that an event or object caused some effect. The latter finding is relevant for event coding, because news coverage often falls into this category.

The “other” class can be considered as a control case, i.e. a label for relationships that seemed relevant to human coders, but did not fit any (or maybe multiple) of the predefined categories. The results for the “other” class do not differ in any meaningful way from the results for the other classes (Table 37). This finding indicates that with respect to windowing, the specific semantic relationships considered in SemEval are representative for other types of relations and vice versa. Taking this interpretation a step further, I argue that we can generalize the insights gained about window sizes for these specific types of semantic relationship to other types of semantic relations for new relation extraction projects.

Finally, I did not find any differences in window size (distribution) depending on the number of examples per relationship. This indicates that coding guidelines used for annotation, the resulting relational data and identified effects, or both, are robust.

In ACE5, more classes of link types are considered than in SemEval; namely syntactic classes, different relationship types (similar to the semantic roles in SemEval) and subtypes, modality, and tense (Consortium, 2005). The first two classes are relevant for this study, and are discussed in detail below. Another important particularity with relations in ACE is that links can be formed between distinct entities that belong to the same extent of one entity. Such constituents are still annotated as truly distinct, individual entities in ACE. For instance, for the marked-up extent of the entity “southern Philippines airport”, there is a relationship (of type “geographical’) annotated between the nominals “airport” (unique entity of type “facility”) and “southern Philippines” (unique entity of type “location”). For practical text coding and event coding applications, users often are often not interested in establishing links among the tokens in multi-word expressions. If those relations do matter, the window size is rather deterministic, i.e. zero for adjacent terms. One goal with this project is to inform decisions about appropriate window sizes between entities that are common in texts from or about socio-technical systems. In such data, relevant mentions of entities typically do not overlap, e.g. in written accounts of who did or said what to whom in what manner. Thus, for the following analyses, it seems necessary to distinguish between relations between overlapping versus non-overlapping entities. Moreover, it seems necessary to discount for deterministic window sizes that result from overlapping entity extents as there is little new to learn about them. My analysis revealed that whether the extents of linked entity mentions overlap or not is mainly a function of the syntactic class[6] of the relationship (Table 38): in ACE5, 67.5% of all links show overlaps in entity extent. Of those

[6] In ACE, one of the intension with syntactic classes is to provide the annotators with a justification or sanity check for marking up a link.

links, 92% are members of three syntactic classes: first, “premod” relations, which denotes links between proper adjectives or proper nouns that modify an entity, e.g. “New York police”. These entities are often multi-word units that an N-gram tagger would identify as such, and for which the window size would be zero. Second, “possessive” relations, where one entity is possessing the other one, e.g. "New York's citizens". These entities are often collocations, and the respective window size would also be zero. Third, “preposition” relations, where two entities are linked through a preposition, e.g. "citizens of New York". Here, the window size equals the number of tokens in the preposition, which is often one or two. Since the window sizes for these three relations are driven by syntactic rules for language production, they are not of further interest for analysis.

Table 38: Types of syntactic relationship, size in corpus, and ratio of overlapping entity extents

Syntactic Relation	Share of total dataset	Overlapping in extent
PreMod	28.2%	99.0%
Verbal	21.2%	4.9%
Preposition	19.4%	88.5%
Possessive	17.3%	98.1%
Other	8.5%	9.4%
Formulaic	3.1%	66.9%
Participial	2.0%	68.6%
Coordination	0.4%	51.6%

Table 39 provides the empiric results for the frequency and coverage rates of window sizes depending on the syntactic relations. “Depending on” here means given a certain window sizes; there could still be some underlying other factor that explains the observed results. These numbers confirm that for possessive and premod relations, the most frequent window size is zero, and over 95% of links in those classes require a window size of two or less.

In other syntactic relations, fewer entities overlap in extent: first, in “coordination” relations, where two nouns phrases are connected via the conjunction “and”, e.g. “citizens and police”. Most of these noun phrases are clearly distinct entities. However, the amount of words between them is still deterministic (one for the “and”, see Table 39 for a confirmation of this rational), and therefore are also not of interest here. Next, “formulaic relations”, which mainly ties the author or reporter and the publishing location of a news article together, such as in “John Doe, the BBC, London”. Here, links also mainly consists of collocated entities so that the most frequent window size is zero (Table 39). Moreover, this genre-specific type of relation cannot be assumed to generalize to other domains, and is therefore disregarded for further analysis.

In relations of the types “participial”, where a participial phrase modifies a head noun, e.g. “the people who moved to New York”, and “verbal”, where nodes are linked through a verb, the involved entities are typically distinct entities, and at least in the case of “verbal” also mainly non-overlapping. Moreover, links of these two types are relevant for event coding as they imply some activity (Gerner, et al., 1994). With some REX approaches, verb phrases that represent activities are actually considered as nodes (K. M. Carley, et al., 2007; Goldstein, 1992; King & Lowe, 2003), while in other approaches, they are not (Corman, et al., 2002). Another syntactic relationship where the majority of instances do not involve overlapping extents of entities is the “other” class. This is a collection of links that do not fit the definition of any of the other syntactic classes, but “beyond a reasonable doubt" are a relevant link (Consortium, 2005). As already explained for the SemEval data, the “other” class is relevant for this study. Taken together, the “participial”, “verbal” and “other” class account for 32.5% of all links in ACE, but only for 4.8% of the links where the extents of entities are overlapping. Based on these results and this reasoning, I consider relations of the types “verbal”, “participial”, and “other” for further analysis, with the exception of the error analysis at the end of this chapter, where all types are considered. For the considered syntactic classes (N of links =2,841), the most common window size is two or three, but it takes more than 7 (participial), 11 (verbal), or 13 (other) intervening words to identify at least 90% of the links (Table 39).

Table 39: Impact of type of syntactic relationship on window size

Window	PreMod		Formulaic		Possessive		Coordination	
0	<u>80.5%</u>	80.5%	<u>75.8%</u>	75.8%	<u>66.8%</u>	66.8%	3.2%	3.2%
1	13.0%	93.5%	12.6%	88.5%	22.9%	89.6%	<u>51.6%</u>	54.8%
2	4.6%	98.2%	4.5%	92.9%	6.4%	96.0%	19.4%	74.2%
3	1.2%	99.4%	2.6%	95.5%	2.6%	98.6%	9.7%	83.9%
4	0.4%	99.8%	1.1%	96.7%	0.7%	99.3%	12.9%	96.8%
5	0.0%	99.9%	0.7%	97.4%	0.3%	99.6%	0.0%	96.8%
6	0.0%	99.9%	0.7%	98.1%	0.2%	99.8%	0.0%	96.8%
7	0.0%	99.9%	0.4%	98.5%	0.1%	99.9%	0.0%	96.8%
8	0.0%	99.9%	0.4%	98.9%	0.0%	99.9%	0.0%	96.8%
9	0.0%	100.0%	0.7%	99.6%	0.1%	99.9%	0.0%	96.8%
10	0.0%	100.0%	0.0%	99.6%	0.0%	99.9%	0.0%	96.8%
	Preposition		**Participial**		**Verbal**		**Other**	
0	1.5%	1.5%	7.6%	7.6%	3.3%	3.3%	9.4%	9.4%
1	<u>37.3%</u>	38.8%	11.0%	18.6%	8.6%	11.9%	8.8%	18.2%
2	31.1%	70.0%	19.8%	38.4%	<u>15.5%</u>	27.4%	<u>12.9%</u>	31.1%
3	14.9%	84.9%	<u>20.9%</u>	59.3%	14.7%	42.1%	10.6%	41.7%
4	6.8%	91.7%	11.6%	70.9%	13.1%	55.2%	10.5%	52.1%
5	3.5%	95.2%	8.7%	79.7%	10.3%	65.5%	8.2%	60.3%
6	1.7%	96.9%	5.8%	85.5%	7.0%	72.5%	6.6%	66.9%
7	1.0%	97.9%	5.2%	90.7%	5.5%	78.1%	6.0%	72.9%

8	0.8%	98.6%	3.5%	94.2%	4.9%	82.9%	4.6%	77.5%
9	0.5%	99.2%	1.2%	95.3%	3.2%	86.2%	4.7%	82.2%
10	0.4%	99.6%	1.2%	96.5%	3.0%	89.2%	2.7%	84.9%

The impact of genre on window size is also of interest here. Table 40 lists the genres considered in this project along with their respective size in the corpus. This table also shows the ratio of the selected syntactic classes among these genres. These numbers show that syntactic relations where window sizes are fairly deterministic are more common in newswire data, while they are slightly less common in broadcast news and telephone conversations; both of which are instances of spoken language.

Table 40: Distribution of genres across corpus and selected syntactic relations (verbal, participial, other)

Genre	All relations	Selected syntactic relations
Broadcast conversation	19.0%	18.9%
Broadcast news	23.1%	25.0%
Newswire	30.7%	23.8%
Telephone	8.5%	12.3%
Usenet	9.9%	11.3%
Weblog	8.8%	8.7%

The most common window sizes (two to three) are similar across all genres (Table 41). Slight exceptions are telephone conversations (about one token shorter windows than cross-genre average), and newswire data (about one token longer windows). The link coverage rates depending on the window size are also very similar across genres, but only until window size eight, where about 80% of all links are found. From there on, the window sizes needed to capture more links start to vary (Table 41).

Table 41: Impact of genre on window size

Win-dow	Broadcast Conversations		Broadcast News		Newswire		Telephone		Usenet		Weblog	
0	6.3%	6.3%	5.5%	5.5%	4.1%	4.1%	4.4%	4.4%	5.4%	5.4%	5.8%	5.8%
1	8.8%	15.1%	9.8%	15.3%	7.4%	11.6%	9.7%	14.1%	9.6%	15.1%	7.4%	13.2%
2	16.7%	31.8%	13.3%	28.6%	11.4%	22.9%	25.2%	39.3%	16.7%	31.7%	10.3%	23.6%
3	14.8%	46.6%	15.0%	43.6%	13.4%	36.3%	13.5%	52.8%	10.3%	42.0%	16.5%	40.1%
4	12.3%	58.8%	13.3%	56.9%	11.4%	47.7%	11.4%	64.2%	14.7%	56.7%	10.3%	50.4%
5	10.0%	68.8%	7.4%	64.2%	9.3%	57.0%	9.7%	73.9%	10.3%	67.0%	15.3%	65.7%
6	6.3%	75.1%	6.8%	71.0%	8.4%	65.3%	5.3%	79.2%	7.1%	74.0%	5.8%	71.5%
7	5.4%	80.5%	6.3%	77.3%	5.3%	70.7%	6.7%	85.9%	3.8%	77.9%	5.8%	77.3%
8	4.6%	85.1%	5.1%	82.4%	5.5%	76.1%	3.2%	89.1%	4.2%	82.1%	4.5%	81.8%
9	3.3%	88.3%	3.6%	86.0%	4.3%	80.4%	2.9%	92.1%	3.5%	85.6%	2.5%	84.3%
10	2.5%	90.8%	3.8%	89.8%	3.3%	83.7%	1.5%	93.5%	2.9%	88.5%	1.2%	85.5%
11	2.3%	93.1%	1.6%	91.3%	1.8%	85.6%	1.5%	95.0%	1.6%	90.1%	2.5%	88.0%

12	0.8%	93.9%	2.2%	93.5%	2.6%	88.1%	1.8%	96.8%	3.2%	93.3%	2.5%	90.5%
13	1.5%	95.4%	2.0%	95.5%	1.7%	89.8%	0.9%	97.7%	1.3%	94.6%	2.5%	93.0%
14	0.6%	96.0%	1.4%	97.0%	1.1%	90.9%	1.2%	98.8%	1.3%	95.8%	0.8%	93.8%
15	1.0%	96.9%	0.7%	97.7%	2.3%	93.2%	0.3%	99.1%	0.3%	96.2%	0.8%	94.6%
16	1.3%	98.3%	0.3%	98.0%	0.8%	93.9%	0.3%	99.4%	0.3%	96.5%	1.2%	95.9%
17	0.4%	98.7%	0.3%	98.3%	0.8%	94.7%	0.3%	99.7%	0.6%	97.1%	0.0%	95.9%
18	0.0%	98.7%	0.1%	98.4%	0.5%	95.1%	0.0%	99.7%	0.6%	97.8%	0.0%	95.9%

The following types of relationships, which are conceptually similar to the semantic relations in SemEval, are analyzed next:

- Social, personal: relations between people.
- Organizational affiliation: professional relations, such as employment.
- General affiliation: relations between people and organizations in the widest sense or geopolitical entities, e.g. residency or religion.
- Agent-Artifact: social agent own an artifact.
- Physical: the location of a person.
- Part whole: the location of objects, hierarchical relations among and between social agents and objects.

Table 42 shows the share of each of these relationships in the entire dataset and among the selected syntactic relations. Grammatically induced window sizes are prevalent in all but the geo-physical and to a lesser degree also in the agent-artifact relations. The results in Table 43 confirm the findings about the semantic relationships in SemEval: typical window sizes (two or three) and coverage rates are very similar across all different types of relationships. The "part-whole" relationship requires a slightly shorter distance, and the same has been observed for the "component-whole" type in SemEval. When filtering the links in ACE5 depending on their type of semantic relationship as done in this study, the average link coverage rates in ACE5 lag behind the rates found in SemEval. One explanation for this difference might be that in ACE, I did eliminate certain grammatical relationships because the window size is deterministic and already know for them. This was not possible for SemEval since no syntactic classification of links was provided there. However, closer inspecting the links with low window size in SemEval suggested that these also represent grammatical dependencies. Therefore, the links in SemEval are a mixture of short, mainly grammatically motivated relations and other types of relations that are of stronger interest here. In ACE, I was able to distinguish between those types of relationships more precisely, showing that the type of grammatical relationship (or lack thereof, as in the "other" type), has a major impact on window sizes.

Table 42: Types of semantic relationships, size in corpus, size among selected syntactic relations

Type	All relations	Selected syntactic relations
Agent-Artifact	10.0%	14.2%
General affiliation	11.0%	5.5%
Organizational affiliation	29.0%	13.8%
Part Whole	14.9%	4.3%
Personal and social	12.5%	7.9%
Physical	22.6%	54.3%

Table 43: Impact of type of semantic relationships on window size

Window	Personal, social		Organizational affiliation		General affiliation		Agent Artifact	
0	3.6%	3.6%	7.1%	7.1%	10.5%	10.5%	1.8%	1.8%
1	9.5%	13.2%	7.3%	14.4%	9.2%	19.7%	7.9%	9.7%
2	17.3%	30.5%	11.5%	26.0%	36.2%	55.9%	17.3%	27.0%
3	10.9%	41.4%	17.3%	43.3%	9.9%	65.8%	15.8%	42.7%
4	11.4%	52.7%	12.6%	55.9%	9.9%	75.7%	14.8%	57.5%
5	10.9%	63.6%	12.6%	68.5%	5.3%	80.9%	8.9%	66.4%
6	4.5%	68.2%	4.5%	73.0%	3.3%	84.2%	7.6%	74.0%
7	8.2%	76.4%	5.2%	78.2%	3.3%	87.5%	5.9%	79.9%
8	5.9%	82.3%	4.7%	82.9%	2.6%	90.1%	5.1%	85.0%
9	4.5%	86.8%	2.4%	85.3%	2.6%	92.8%	2.3%	87.3%
10	1.8%	88.6%	3.7%	89.0%	1.3%	94.1%	2.0%	89.3%
11	1.4%	90.0%	2.1%	91.1%	0.0%	89.0%	1.5%	90.8%
12	1.4%	91.4%	2.4%	93.4%	2.0%	96.1%	1.8%	92.6%
13	0.9%	92.3%	1.3%	94.8%	1.3%	97.4%	2.0%	94.7%
14	2.7%	95.0%	0.3%	95.0%	0.7%	98.0%	0.8%	95.4%
15	1.8%	96.8%	0.5%	95.5%	0.0%	98.0%	1.0%	96.4%
	Part Whole		Physical		Average			
0	7.6%	7.6%	5.1%	5.1%	6.0%	6.0%		
1	5.9%	13.6%	9.5%	14.6%	8.2%	14.2%		
2	11.0%	24.6%	13.2%	27.9%	17.8%	32.0%		
3	12.7%	37.3%	13.6%	41.5%	13.4%	45.3%		
4	12.7%	50.0%	12.0%	53.5%	12.2%	57.5%		
5	9.3%	59.3%	9.3%	62.8%	9.4%	66.9%		
6	7.6%	66.9%	7.8%	70.6%	5.9%	72.8%		
7	5.9%	72.9%	5.5%	76.1%	5.7%	78.5%		
8	4.2%	77.1%	4.7%	80.8%	4.5%	83.0%		
9	6.8%	83.9%	3.8%	84.6%	3.7%	86.8%		
10	5.1%	89.0%	2.9%	87.5%	2.8%	89.6%		
11	0.0%	89.0%	2.3%	89.8%	1.2%	89.9%		
12	3.4%	92.4%	2.1%	91.9%	2.2%	93.0%		
13	0.0%	92.4%	1.9%	93.8%	1.3%	94.2%		
14	2.5%	94.9%	1.1%	94.9%	1.3%	95.5%		
15	1.7%	96.6%	1.1%	96.0%	1.0%	96.6%		

Most of the types of relationships discussed in the previous paragraph are defined over entity types, i.e. they can only be established between certain node classes. In this sense, semantic relationships are a proxy for the impact of the classes of nodes involved in a link on the window size. We can determine this impact even more precisely by analyzing the window size for all combinations of node classes for which the data denote a link[7]. Table 44 shows how these types of links are distributed across the corpus. The vast majority of these links (over 85%) occur between a person and a) another person (7.5% of all links) or b) some other entity class (77% of all links). Only four percent of all links do not involve a social agent (person or organization). Therefore , the findings from this analysis are highly relevant for constructing social network data (person to person) and socio-technical network data (social agents to some other entity type). Looking at window sizes from perspective, again, the common window sizes and coverage rates are highly similar across (Table 45). The exceptions are "person-time" relations, where the window size is about two tokens longer than for the other types, and "location-location" relations, which are shorter than the average by about one token. Looking at aggregated groups of node classes with respect to link coverage rates, the results suggest that the rates grows fastest for spatial relations (window sizes here are comparatively shorter than for the other groups, size 10 for 90% of the links), followed by relations between social agents and resources (Table 45). For relations between social agents only, average window sizes are comparatively longest (12 for 90% of the links). However, these differences are still small.

Table 44: Links per entity class

Entity Class	Person	Organization	Location	Resource	Time
Person	7.5%	18.7%	34.9%	6.6%	16.8%
Organization	0.5%	2.5%	1.7%	3.6%	0.7%
Location	1.4%	0.7%	3.6%	0.0%	0.0%
Resource	0.3%	0.0%	0.0%	0.3%	0.0%
Time	0.0%	0.0%	0.0%	0.0%	0.0%

[7] The entity classes in ACE are: person, organization, geopolitical entity (GPE), location, facility, vehicle, and weapon. In order to keep the findings comparable to further analyses on the node class level (chapters 4 and 5), I mapped the ACE classes to the meta-network classes as follows: Agent: person. Organization: organization and GPE except for population center and state. Location: location, GPE (except for country, GPE cluster, nation, continent, special) , and facility. Resource: vehicle and weapon.

Table 45: Impact of entity class on window size*

Window	Person Person		Person Organization		Person Location		Person Resource		Person Time	
0	3.4%	3.4%	5.6%	5.6%	5.1%	5.1%	2.1%	2.1%	7.1%	7.1%
1	8.7%	12.0%	9.8%	15.4%	7.9%	12.9%	7.8%	9.9%	11.0%	18.1%
2	18.8%	30.8%	15.4%	30.8%	16.7%	29.7%	16.1%	26.0%	7.1%	25.2%
3	11.5%	42.3%	16.0%	46.8%	15.1%	44.8%	19.8%	45.8%	8.4%	33.5%
4	11.5%	53.8%	11.1%	57.9%	13.6%	58.5%	14.1%	59.9%	9.9%	43.4%
5	11.1%	64.9%	11.7%	69.5%	7.9%	66.3%	8.9%	68.8%	10.3%	53.8%
6	4.3%	69.2%	6.0%	75.6%	8.1%	74.4%	7.3%	76.0%	6.2%	60.0%
7	7.2%	76.4%	5.1%	80.6%	5.9%	80.3%	5.7%	81.8%	6.0%	66.0%
8	5.8%	82.2%	4.7%	85.3%	3.7%	84.0%	4.7%	86.5%	6.5%	72.5%
9	4.3%	86.5%	2.4%	87.8%	3.8%	87.7%	0.5%	87.0%	3.9%	76.3%
10	1.9%	88.5%	3.2%	91.0%	2.2%	89.9%	2.1%	89.1%	4.3%	80.6%
11	1.4%	89.9%	1.3%	92.3%	2.3%	92.2%	1.0%	90.1%	3.2%	83.9%
12	1.4%	91.3%	2.6%	94.9%	1.9%	94.1%	2.6%	92.7%	2.2%	86.0%
13	1.0%	92.3%	1.5%	96.4%	1.7%	95.8%	1.6%	94.3%	2.6%	88.6%
14	2.9%	95.2%	0.8%	97.2%	0.7%	96.5%	1.0%	95.3%	1.1%	89.7%
15	1.4%	96.6%	0.4%	97.6%	0.9%	97.4%	0.5%	95.8%	2.4%	92.0%
	Organization Organization		**Organization Resource**		**Organization Location**		**Location Location**		**Average (unweighted)**	
0	2.9%	2.9%	1.0%	1.0%	9.1%	9.1%	5.9%	5.9%	4.7%	4.7%
1	4.3%	7.2%	6.0%	7.0%	10.6%	19.7%	7.9%	13.9%	8.2%	12.9%
2	20.3%	27.5%	24.0%	31.0%	15.2%	34.8%	12.9%	26.7%	16.3%	29.2%
3	13.0%	40.6%	10.0%	41.0%	13.6%	48.5%	16.8%	43.6%	13.8%	43.0%
4	10.1%	50.7%	11.0%	52.0%	15.2%	63.6%	11.9%	55.4%	12.0%	55.0%
5	10.1%	60.9%	9.0%	61.0%	10.6%	74.2%	11.9%	67.3%	10.2%	65.2%
6	4.3%	65.2%	9.0%	70.0%	4.5%	78.8%	7.9%	75.2%	6.4%	71.6%
7	5.8%	71.0%	6.0%	76.0%	0.0%	78.8%	5.9%	81.2%	5.3%	76.9%
8	4.3%	75.4%	4.0%	80.0%	4.5%	83.3%	5.0%	86.1%	4.8%	81.7%
9	5.8%	81.2%	7.0%	87.0%	6.1%	89.4%	3.0%	89.1%	4.1%	85.8%
10	5.8%	87.0%	3.0%	90.0%	1.5%	90.9%	3.0%	92.1%	3.0%	88.8%
11	0.0%	87.0%	1.0%	91.0%	0.0%	90.9%	0.0%	92.1%	1.1%	89.9%
12	1.4%	88.4%	1.0%	92.0%	3.0%	93.9%	3.0%	95.0%	2.1%	92.1%
13	0.0%	88.4%	4.0%	96.0%	0.0%	93.9%	0.0%	95.0%	1.4%	93.4%
14	5.8%	94.2%	0.0%	96.0%	0.0%	93.9%	1.0%	96.0%	1.5%	94.9%
15	1.4%	95.7%	1.0%	97.0%	0.0%	93.9%	1.0%	97.0%	1.0%	95.9%

* Only type of entity to entity connections with 20 or more links considered. Relations are directional in the data. Here, both directions are taken together per type.

Table 46 provides a brief summary of the results from the windowing analysis reported in this chapter. This synopsis shows that after controlling for the type of syntactic relationship, i.e. excluding relationships where the window sizes are short and deterministic due to syntactic rules of language production, there are virtually no differences between typical window sizes and link

coverage rates across different genres, other types of syntactic relationships, types of semantic relationships, and types of node classes involved in links.

Table 46: Summary of results for windowing

		SemEval	ACE5			
		Semantic relations	Syntactic relations	Semantic* relations	Node class*	Genre*
Most frequent window size		2	2	2	2	2 and 3
Link coverage rate	50%	3	4	4	4	4
	75%	5	7	7	7	7
	80%	5	8	8	8	8
	90%	7	10	12	12	11
	95%	8	13	14	14	14

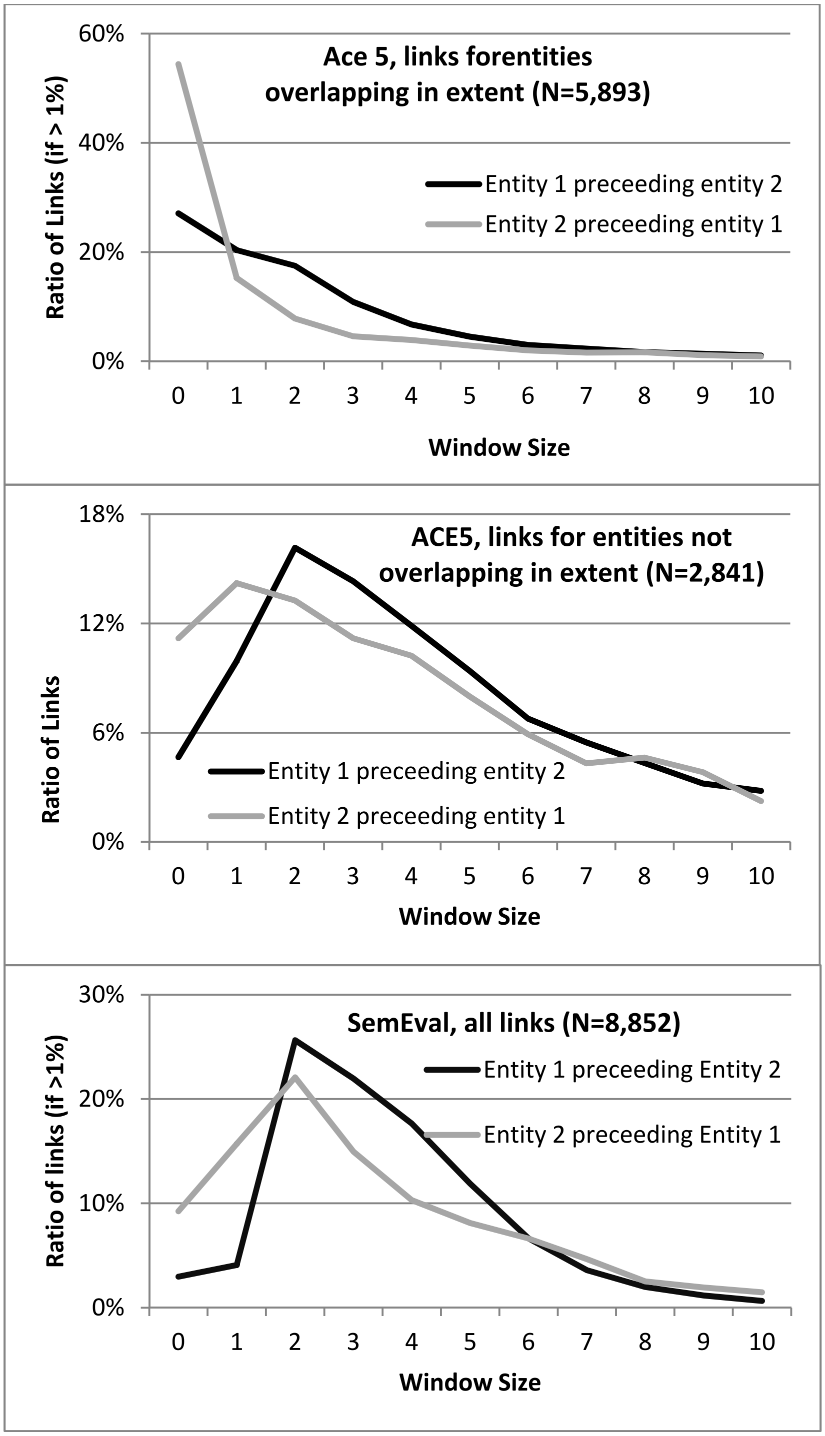
* controlled for type of syntactic relation (only including verbal, participial, other)

Finally, the data show an impact of entity ordering on window size: in more than half of all links, the first entity in a relationship precedes the second one (55% of all links in SemEval[8], 58% in ACE). If this is the case, the average window size is about one word longer than when the second entity precedes the first one (Figure 8). This ordering effect disappears at about window size six, and is similar across all types of relationships, nodes in links, and both corpora.

The results in Figure 8 also show that for linked entities with non-overlapping extents (ACE5), the patterns of link coverage rates depending on window size are highly similar for both corpora. This holds true even though these two corpora differ considerably in genres, time of data collection, and types of entities and relations considered. Therefore, this result suggests that the presented results for typical window sizes and amount of links identified depending on the window size are highly robust across genres, time, data sources, and types of relationships. This implies that the window sizes found with this study are likely to generalize to other text data.

[8] The analysis of order effects excludes the “other” relationship because no entity order is marked up for these relations.

Figure 8: Impact of ordering effects on window size and link coverage



2.7.2.2 Evaluation of windowing

Using windowing for connecting nodes into edges implies the danger of missing links (false negatives) and retrieving incorrect links (false positives). This potential cause of errors has been

repeatedly pointed out in the past (K.M. Carley, 1997a; Corman, et al., 2002), but has not yet been empirically tested. I am quantifying the amount of these errors based on the SemEval and ACE5 data.

The results show that the rates of false negatives decline rapidly; falling below 5% at window size 8 (SemEval) or 9 (ACE, text-level, all types of relations considered). At window size 12, the rate of false negatives is less than 2.4% (ACE5) to 1% (SemEval) (Table 47, Table 48, Table 49). Table 47 and Table 48 express these errors in terms of false positives and false negatives, and Table 49 represents the same errors in terms of recall, precision, and the harmonic mean of these two metrics (F).

Table 47: Accuracy rates and false negatives due to windowing (SemEval)

Window Size	Correct	False Negatives
0	5.9%	94.1%
1	15.2%	84.8%
2	38.8%	61.2%
3	57.8%	42.2%
4	72.3%	27.7%
5	82.5%	17.5%
6	89.1%	10.9%
7	93.2%	6.8%
8	95.4%	4.6%
9	97.0%	3.0%
10	97.9%	2.1%
11	98.6%	1.4%
12	99.1%	0.9%

The rate of false positives was measured by connecting the heads of any nodes that are annotated as entities in the ground truth data if the number of tokens between these heads is equal to or lower than a given window size. This was done for ACE5, but could not be done for SemEval because there, only two entities are marked up per sentence, and the sentences are not consecutive. The links in ACE5 are mainly marked up within sentences. However, 4.2% of all links span across sentences. For real world applications, considering cross-sentence links can be an appropriate approach, e.g. when an event is described over multiple sentences[9]. In order to clarify on the impact of distinguishing between within versus across sentence links, I show the results for both scenarios in Table 48 and Table 49: for the lower halves of these tables, windows were reset at the end of sentences. A side effect of this distinction is that with the sentence level approach, the rate of false negatives (7.2% at window size 12) will be higher since some links

[9] In order to accommodate for that in AutoMap, users there can chose the number of sentences after which the window should be reset.

cannot be found within sentences. Sentences splitting was conducted by considering each dot as a sentence mark unless the dot occurs right next to a list of 86 terms (e.g. Dr., D.C.) that I identified by checking all actual cross-sentence links in ACE. This way of sentence splitting is on the conservative side, i.e. there might be more sentences identified than there really are. I chose this approach to make sure that the number of false positives is not overestimated. Therefore, my results show the lower bound of false positives due to windowing in addition to the more unconstrained, cross-sentence setting.

Overall, the rate of false positives is alarmingly high. When considering all additional links retrieved, the rate of false positives is similar to the rate of correctly identified links. For example, at window size 7, 88.9% (sentence level) to 92.5% (cross-sentence level) of false positives are returned (Table 48 , 4th column). This means that when a window size of 7 is applied, 9 out of 10 of the retrieved links were not annotated by human coders as being relevant.

Table 48: Error rates for windowing I (ACE5)

Window Size	Correct	False Negatives	False Positives		
			All	Restriction 1	Restriction 2
	Text level (resembling ground truth)				
0	38.6%	61.4%	55.3%	36.6%	19.2%
1	56.7%	43.3%	73.4%	60.7%	37.2%
2	70.2%	29.8%	81.1%	73.1%	52.0%
3	78.3%	21.7%	85.4%	79.6%	61.1%
4	83.9%	16.1%	88.1%	83.7%	58.2%
5	87.7%	12.3%	90.0%	86.5%	72.3%
6	90.3%	9.7%	91.4%	88.5%	76.0%
7	92.4%	7.6%	92.5%	90.0%	78.8%
8	94.0%	6.0%	93.3%	91.1%	81.0%
9	95.2%	4.8%	94.0%	92.1%	82.8%
10	96.3%	3.7%	94.5%	92.8%	84.3%
11	96.9%	3.1%	95.0%	93.4%	85.5%
12	97.6%	2.4%	95.3%	94.0%	86.6%
	Sentence level				
0	35.3%	64.7%	48.0%	26.5%	11.9%
1	53.0%	47.0%	67.6%	52.8%	28.1%
2	66.1%	33.9%	76.2%	65.1%	40.5%
3	74.1%	25.9%	81.0%	72.6%	50.0%
4	79.6%	20.4%	84.0%	77.3%	56.6%
5	83.3%	16.7%	86.2%	80.5%	61.8%
6	85.8%	14.2%	87.7%	82.9%	65.8%
7	87.8%	12.2%	88.9%	84.6%	68.9%
8	89.4%	10.6%	89.8%	85.9%	71.2%
9	90.5%	9.5%	90.5%	87.0%	73.1%
10	91.5%	8.5%	91.1%	87.8%	74.6%

11	92.1%	7.9%	91.5%	88.5%	76.0%
12	92.8%	7.2%	91.9%	89.1%	77.1%

Table 49: Error rates for windowing II (ACE)

Window Size	Recall	All false positives		Restriction 1		Restriction 2	
		Precision	F	Precision	F	Precision	F
	Text level (resembling ground truth)						
0	38.6%	17.3%	23.8%	24.4%	29.9%	31.2%	34.5%
1	56.7%	15.1%	23.8%	22.3%	32.0%	35.6%	43.7%
2	70.2%	13.3%	22.3%	18.9%	29.8%	33.7%	45.6%
3	78.3%	11.4%	20.0%	16.0%	26.6%	30.5%	43.9%
4	83.9%	10.0%	17.8%	13.7%	23.5%	35.1%	49.5%
5	87.7%	8.7%	15.9%	11.9%	20.9%	24.3%	38.1%
6	90.3%	7.7%	14.2%	10.4%	18.6%	21.7%	34.9%
7	92.4%	6.9%	12.9%	9.2%	16.8%	19.6%	32.3%
8	94.0%	6.3%	11.8%	8.3%	15.3%	17.9%	30.1%
9	95.2%	5.7%	10.8%	7.6%	14.0%	16.4%	28.0%
10	96.3%	5.3%	10.0%	6.9%	12.9%	15.1%	26.2%
11	96.9%	4.9%	9.3%	6.4%	11.9%	14.0%	24.5%
12	97.6%	4.5%	8.7%	5.9%	11.1%	13.1%	23.0%
	Sentence level						
0	35.3%	18.3%	26.0%	31.1%	24.1%	29.9%	33.1%
1	53.0%	17.2%	25.0%	38.1%	25.9%	34.0%	44.3%
2	66.1%	15.7%	23.1%	39.3%	25.4%	34.2%	49.3%
3	74.1%	14.1%	20.3%	37.1%	23.7%	31.9%	49.4%
4	79.6%	12.7%	18.1%	34.5%	21.9%	29.5%	48.1%
5	83.3%	11.5%	16.2%	31.8%	20.3%	27.2%	46.1%
6	85.8%	10.5%	14.7%	29.3%	18.8%	25.1%	43.7%
7	87.8%	9.8%	13.5%	27.3%	17.6%	23.4%	41.7%
8	89.4%	9.1%	12.6%	25.7%	16.6%	22.0%	40.0%
9	90.5%	8.6%	11.8%	24.4%	15.7%	20.9%	38.4%
10	91.5%	8.2%	11.1%	23.2%	15.0%	19.9%	37.0%
11	92.1%	7.8%	10.6%	22.1%	14.4%	19.0%	35.7%
12	92.8%	7.5%	10.1%	21.3%	13.8%	18.3%	34.6%

Further analyzing the false positives revealed that in many cases, the entities were overlapping. As mentioned previously in this chapter, such entities often represent regular multi-word expressions, e.g. "UN Security Council", or consist of a named entity plus a role or attribute of the entity, e.g. "Palestinian security sources". However, for practical relation extraction purposes, users would typically not create links within meaningful N-grams, and roles and attributes are often not considered as a node class of their own, but only as attributes of nodes. Therefore, I conducted a second analysis of false positives were I excluded any links between overlapping entity extents from counting the false positives. This experimental condition is

referred to as restriction 1 in Table 48 and Table 49. After applying this restriction, the remaining false positives contained a large number of entities from the node class “time” (timex), such as dates and clock time. Since these entities never have a head but only an extent, which could span more tokens that the heads of other entities, I also excluded the timex entities in restriction 1. Another sizable portion of entities involved in false positives were references to media organizations, which typically occur at the beginning or end of news articles. Since these entities are atypical in genres other than news data, they were also disregarded in restriction 1. Overall, applying restriction 1 lowers the number of false positives per window size by thousands of links. However, at window size 7, there are still 84.6% to 90.0% of links that are false positives (Table 48).

Further analyzing the remaining false positives showed that many entities involved were pronouns. Therefore, I introduce restriction 2, which assumes that anaphora resolution had been applied prior to relation extraction as follows: pronouns get translated into entities that are referred to by a name or nominal, and a legitimate link from such an entity to another entity already exists, such that the false positive would only increase the weight of an existing link. For details on the impact of anaphora resolution on network data see the previous results section. This is a very optimistic assumption, and is meant to show the lower bound for false positives due to windowing, even though this might be an underestimation. Applying restriction 2 in addition to restriction 1 further cuts the rate of false positives to less than the rate of correct links, but the false positives still exceeds 68.9% to 84.6% at window size 7, and further increase from there on (Table 48).

Further inspecting the remaining false positives suggested that these were not connections between named entities and roles or attributes associated with these entities. Also, the remaining false positives did not seem to be other types of meaningful relations that were emerging or discovered from the data, but rather random connection between nearby entities that did not seem obviously reasonable.

The results in Table 49 show that when using windowing, recall is acceptably high - over 90% from window size 6 (cross-sentence level) to 9 (sentence level) on. Note that recall is not impacted by applying the restrictions explained in the previous paragraph. However, the harmonic mean of recall and precision is fairly low due to the low precision rates; not exceeding 18% at window size 7.

2.7.2.3 Windowing: Answers to research questions

The empirical results from the windowing study suggest the following answers to the research questions:

1. Question: What window sizes do experts human use when identifying relations in text data? Does the typical window size differ depending on the type of data or relations?

1. Answer: Regardless of text genre and the type of semantic relationship, syntactic relationship, and node classes, the most frequently used window size is two.

2. Question: What window size is needed to capture the vast majority of links in text data? Does this size differ depending on the type of data or relations?

2. Answer: On average and regardless of text genre and the type of semantic relationship, syntactic relationship, and the classes of nodes involved in a link, at least 50% of all links are found when using a window size of four. After that, window sizes vary depending on the type of syntactic relationship: for mainly syntactically motivated relations, it is sufficient to choose a window size of four to retrieve over 90% of the links. Excluding these syntactic relations, a window of at least twelve is needed to achieve the same result. If a corpus contains an indistinguishable mixture of both types of links; at least 90% of all links are covered with a window size of seven. After controlling for the type of syntactic relationships, i.e. excluding relationships where the window size is short and deterministic due to syntactic rules of language production, these findings are robust across text genres, types of semantic relationships, and node classes. In summary, meaningful differences between link coverage rates are due to syntactic relations. Finally, window sizes also differ depending on ordering effects of the occurrence of entities in the text data. The latter effect is also robust across the test corpora.

3. Question: What error rate, i.e. amount of wrongfully identified links (false positives) and missed links (false negatives), can be expected when applying a specific window size? Does the error rate differ depending on the type of data or relations?

3. Answer: Based on the ground truth datasets used herein, the rate of false negatives declines rapidly; falling below 5% at window size eight to nine. At window size twelve, the rate of false negatives is 2.4% (excluding certain abovementioned syntactic relations) to less than 1% (incl. those syntactic relations). However, the rate of false positives is alarmingly high: when coding links across sentences, the rate of false positives ranges between 79% to 93% at window size seven, and 87% to 95% at window size twelve. When coding links only within sentences, the rate of false positives varies between 69% to 89% at window size seven, and 77% to 92% at

window size 12. The variances in range are due to eliminations of certain types of entities involved in false positives. Therefore, the presented results can be interpreted as an empirically grounded upper bound and lower bound for the rates of false positives due to windowing.

2.8 Conclusions

The results from reference resolution project and the windowing project show that the coding choices that need to be made when extracting entities and relational data from texts strongly impact the network properties and structure. The conclusions from the experimental work are presented in this section. The practical implications of the findings from this chapter for applied work are synthesized in chapter 4.

The goal with RR is to map pronouns and additional entity mentions to the set of unique entities; thereby reducing the amount of pronouns and unassociated entities while increasing the weight per unique entities. The results from the RR study indicate that the deduplication, consolidation and personalization of entities has a strong impact on the node, link and network level, especially with respect to quantitative analysis results: applying both, AR and CR, alters the identity and weight of about 76% of all entity mentions, and the average weight per unique entity or node is increased from 1.0 to 5.8. As a result, less than 18% of the unique nodes carry more 79% of the total node weight. The impacts are less strong on the link level: In about 23% of all links, at least one node is changed due to AR, and 6% of all links are reduced via CR. Combining both techniques leads to a link reduction of 12%. Of the remaining links, 11% are changed due to RR, and they carry 23% of the total link weight. On the network level, the values of several metrics change strongly when applying RR, for example degree centralization, clustering coefficients, and connectedness (all increased), while a smaller number of metrics is not impacted, e.g. fragmentation, efficiency and hierarchy. In comparison to the raw data, the set of key players identified through network analysis completely changes when applying AR and CR; with CR having a stronger impact on the outcome. For all observed effects, combining AR and CR is more effective than applying either technique alone.

The ratios of resolvable anaphora as well as entities that can be co-referenced are similar across all genres considered. However, the impact of either technique on a corpus from a given domain varies depending on the distributions of pronouns, names, and nominal: in newswire and newspaper data, names and nominals are dominating, and therefore, CR is more effective than AR. In telephone conversations, where pronouns are dominating, AR makes a bigger difference than CR does. In social media data, the difference in the effectiveness per technique is more balanced, and both techniques together are highly effective (74% of entities changed).

The findings from simulating the impact of typical error rates for RR on changes in the resulting network data show that the amount of change in the value of network analytical metrics by far exceeds the change rate in RR accuracy (for 13 of 20 measures tested). The set of the nodes that score highest on these metrics is more robust towards changes in RR accuracy.

The results from the impact of windowing on link formation show that expert human coders typically apply short window size, which are mainly two to three words long. A window size of twelve is sufficient to identify more than 90% of all links in the ground truth data. These findings are robust: after disregarding relationships where the window sizes are deterministic due to syntactic rules of language production, there are virtually no differences between typical window sizes and link coverage rates across different datasets, genres, types of syntactic relationships, types of semantic relationships, and types of node classes involved in links.

The error analysis of links found by using windowing revealed that the amount of false negatives (missing links) is low; falling below 5% at window sizes eight to nine. However, the rate of false positives (additional links retrieved) is alarmingly high; reaching 90% at window size five. The rate of false positives shrinks when corpus-specific peculiarity of annotating entities and relations are disregarded, but still reaches 90% at window size seven. Assuming that AR would have been applied to the data such that no pronouns are left in any link further reduces the rate of false positives to 87% at window size twelve.

2.9 Limitations and Future Work

The insights gained with the reference resolution study and the windowing study strongly depend on the data. Even though multiple datasets were reviewed for their eligibility for this study, and multiple datasets have been analyzed, other data might have lead to different results, or provide further support for the presented findings.

The findings on the joint impact of AR and CR are furthermore limited by the order of the application of these routines. I used AR prior to CR, and this reflects common practice. With this approach, the amount of non-pronominal entities is increases first, which can then be exploited by CR. However, performing CR first might result in a less confusing mass of entities to choose from for AR. Further work is needed to identify the optimal ordering of AR and CR.

One could argue that the shown differences in the values of network analytical measures depending on RR techniques are influenced by the size of the network. In fact, prior research has shown how robust certain network metrics towards missing data and thus network size (Borgatti, Carley, & Krackhardt, 2006). However, the RR techniques impact the network size in the first

place. Therefore any identified changes might still correlate with changes in network size, but the driving underlying mechanism is still the applied RR techniques.

The RR study has shown how RR techniques help to bring network data extracted from texts closer to the true underlying network structure. A valuable extension to this work would be to use network analysis to identify the structural position and properties of nodes on which reference resolution would be most effective, such as frequently mentioned pronouns or agents that are often referred to by different names – even this assumption would need to be tested. For example, AR can cause the split-up of highly central yet generic nodes, such as "he" and "they", into multiple and distinct names and nominals. The question here is: are the properties of these nodes distinct from other nodes and can thus be identified with network analysis? The outcome of such an extension could be a mechanism that suggests nodes for further treatment with RR to the user.

Finally, two preprocessing techniques and one link formation technique that are applicable when coding texts as networks were investigated. These techniques were selected because they are commonly used. Moreover, co-reference resolution and windowing are available in AutoMap, but we did not have a clear understanding of their impact on the networks extracted with AutoMap. In order to gain a more comprehensive understanding of the impact of coding choices on network data and analysis results, more techniques need to be investigated, especially alternative link formation approaches, such as techniques based on syntax and semantics of text data.

3 Computational Integration of Network-Centric Classification Model and Supervised Machine Learning for Entity Extraction

3.1 Introduction and Problem Statement

One key step in Relation Extraction is the extraction of entities from text data, which are then used as nodes for constructing network data (A. McCallum, 2005). These entities or nodes are referred to as concepts, which are abstract representations of what people conceive in their minds (J. F. Sowa, 1984). Extracting entities from texts also exists as a standalone task, which is referred to as Entity Extraction. Methods for solving this task differ depending on what type of network data need is needed:

For generating one-mode networks form texts, it is sufficient to correctly locate the relevant entities in text data and then linking them into edges (K.M. Carley, 1994; J. A. Danowski, 1993). The resulting networks are often called concept networks, and sometimes also semantic networks (Diesner & Carley, 2011). To keep terminology coherent in this document, I refer to relational representations of language and knowledge as concept networks (for a review of methods for constructing networks of words see J. Diesner & K. M. Carley, 2010b; for a brief synopsis see Diesner & Carley, accepted). One-mode concept networks have been typically used to answer questions like: What concepts, topics or memes emerge, spread and vanish in socio-technical networks? How do such diffusion processes happen? (Corman, et al., 2002; Doerfel & Barnett, 1999; P Gloor, et al., 2009; Griffiths, et al., 2007; J. Leskovec, et al., 2009) Sometimes, the nodes in such networks are further connected to nodes representing the agents who have generated the information represented by the concept nodes, or the documents in which this information occurred. Such networks are often constructed as bipartite graphs, and haven been used to address questions like: Who is talking to whom about what? Who is setting what trends? Who is an expert on which topic? (Ehrlich, Lin, & Griffiths-Fisher, 2007; Giuffre, 2001; PA Gloor & Zhao, 2006; C. Roth & Cointet, 2010; Shahaf & Guestrin, 2010)

For building multi-mode networks, the located entities further need to be assigned to entity classes, which are also known as categories. This assignment typically happens according to some ontology, which can be predefined or derived from the data (Van Atteveldt, 2008). State of the entity extraction and relation extraction technologies typically facilitate the retrieval of named and unnamed mentions of the entity classes of *people*, *organizations*, *locations* and *miscellaneous* or *other* entities (Borthwick, Sterling, Agichtein, & Grishman, 1998; P. Schrodt, 2001). The resulting network have been used to address questions like: Who is talking to whom? Who are the key players in a group? What opportunities and challenges result from the observed

structure and properties of a network for an organization or a social system? (K. M. Carley, et al., 2007; Hämmerli, et al., 2006; Van Atteveldt, 2008)

Accuracy rates for NER systems have steadily increased over the last decade; being in the 80ies and lower 90ies for English (see for example Florian, Ittycheriah, Jing, & Zhang, 2003). Since such systems often focus on the extraction of entities that are referred to by a name, this process is also called Named Entity Recognition (NER) (D. M. Bikel, Miller, Schwartz, & Weischedel, 1997; Klein, Smarr, Nguyen, & Manning, 2003; Ratinov & Roth, 2009). In NLP and political science, the default set of types of named entities to extract has remained fairly unchanged over the last decade. However, for studying the properties and functioning of socio-technical networks, and addressing substantial questions about networks and their context, the classic set of entity classes might not suffice: in addition to knowing which social agents and locations are relevant and connected, one might also need relational data about the what (*tasks* and *events*), how (*resources* and *knowledge*), why (*beliefs* and *sentiments*) and when (*time*) of interactions and activities (Barthelemy, et al., 2005; K.M. Carley, 2002a). Since mentions of instances of these additional entity classes are often not referred to by a name, I refer to the more general task of extract named and unnamed entities as "entity extraction". Entity Extraction allows for the construction richer multi-mode data than NER does. The data resulting from Entity Extraction allow us to move beyond asking questions about social networks, other types of one-mode networks, and bipartite graphs in which one type of nodes are agents, to also address questions like: Which tasks and events are the key players of a group involved in? What resources and knowledge are at the agents' disposal, and what impact does resource allocation have on task completion? What is the interplay of social and technical structures, and how do these structures co-evolve? (K.M. Carley, 2002a; Cataldo, Wagstrom, Herbsleb, & Carley, 2006; D. Krackhardt & Carley, 1998) Also, for sentiment analysis and social media analysis - two subareas of Information Extraction that are currently highly popular and gaining further momentum - such additional categories are essential for analyzing individual and collective behavior (see for example Qureshi, Memon, Wiil, & Karampelas; Whitelaw, Patrick, & Herke-Couchman, 2006).

Looking at NER solutions from the perspective of end-users who want to apply these systems to their data with the purpose of investigation socio-technical phenomena in networks, there is another shortcoming: from an NLP perspective, efforts in advancing NER have been focused on improving the accuracy and efficiency of extractors, while transitioning from learned models to readily usable end-user NER technologies has gotten less attention in reports about cutting edge solutions. This is perfectly reasonable when considering that the goal with such projects is often to develop highly accurate and efficient algorithms, e.g. for participating in competitions where performance on a specific shared test data set is the main assessment criterion.

In summary, there is an unsatisfied need among researchers and practitioners for being able to extract entities beyond the classic set of named entities from text data in an efficient and predictably accurate fashion for the purpose of construction multi-mode network data that allow for answering substantial question about socio-technical networks (Barthelemy, et al., 2005; Parastatidis, et al., 2009; C. Roth, 2006). This thesis addresses this need by devolving a computational solution to this issue (this chapter) and demonstrating its application to analyzing a particular, large-scale network on which no data is readily available otherwise and cannot be efficiently collected with alternative methods (next chapter): based on the outlined shortcomings, I start by developing a set of requirements for an entity extractor (3.2.2). Next, I review the various methods that are available for conducting entity extraction (3.2.3) and select the method that is most suitable given the identified requirements. Then I describe how I adapted and further advanced a technology that implements this method (3.3), and report on the performance of the resulting technology (3.4). Chapter 5 puts the outcome of this work in an application context by using the resulting prediction models to distill network data representing links between various entity types in the country of Sudan from a corpus of open source documents from mainly from news wire data.

3.2 Goal Definition, Requirement Specification, and Strategies for Achieving Objectives

The goal and deliverable for this project is an entity extractor that end-users can employ in the process of constructing multi-mode, socio-technical network data from texts. To provide end-users with this technology, I integrate it into the AutoMap software, where this new functionality is expected to improve the status quo of entity extraction. The extracted entities can then be used to construct concept networks and to conduct content analysis. The network data resulting from this process can be further analyzed with tools such as ORA. The ORA software is tuned for the kind of network data and ontological text coding that AutoMap supports (Kathleen M. Carley, Reminga, Storrick, & Columbus, 2011).

From an NLP perspective, the research question that typically drives the development of entity extractors is typically formulated like this: How can we build or improve an entity extraction algorithm or system that leads to the comparatively most accurate results? Points of comparison are typically a baseline and/or the best-performing alternative solution. In this thesis, I shift the focus from further gains in accuracy to gains in the practical usefulness of the extracted data for conducting network analysis. Thus, my research question for this chapter is this: How can we build an entity extractor as part of a relation extraction system that supports users in analyzing networks *and* addressing substantial questions about socio-technical networks? From a network

analysis perspective, this question has to be answered before the NLP-oriented question becomes applicable. It is important to highlight that this research question does not contradict with the one typically asked in NLP; both questions are critical. Rather, my question complements the one asked in NLP because accuracy is one among multiple important criteria for entity extraction; yet other criteria include the appropriateness of coding schemes and methods for analyzing the resulting data (P. Schrodt, 2001).

In the next section, I formalize the given task: I describe how entity extraction and node linkage are currently handled in AutoMap (3.2.1), then define the requirements for a new entity extractor (3.2.2), and develop a solution to each requirement (3.2.3 to 3.2.6).

3.2.1 Status Quo of Entity Extraction in AutoMap

AutoMap is a text mining tool that provides routines for information extraction and relation extraction (for a detailed description of AutoMap see K. M. Carley, et al., 2007; Diesner & Carley, 2004). In AutoMap, concept networks are called semantic networks, and multi-mode networks are called meta-networks (K.M. Carley, D. Columbus, et al., 2011). The method used for coding text as networks in AutoMap was originally called "map analysis" (K.M. Carley, 1993); a reflection of its purpose to extract mental models of individuals and teams from texts (K.M. Carley, 1997a; K.M. Carley & Palmquist, 1991). Later, the method was referred to more generally as "network text analysis" (NTA), which basically works as follows (K.M. Carley, 1997b; Popping, 2003): the user creates a thesaurus that associates terms as they occur in the text data with user-defined concepts that represent variables of interest. The software assists the user in this process, e.g. by suggesting a set of relevant terms according to (weighted) term frequencies. Concepts represent the pieces of information that are necessary for answering a research question; similar to codes in qualitative text coding (H. Bernard & Ryan, 1998). The software then applies the thesaurus to the text data by translating any matching terms into the respective concepts. Finally, the concepts are linked by using a proximity-based approach (J. A. Danowski, 1993). The main assumption with map analysis and NTA is that these methods support the extraction of meaning from texts by finding or establishing links between concepts and conducting network analysis of the resulting data (K.M. Carley, 1994, 1997b; Mohr, 1998; Monge & Contractor, 2003; Popping, 2003; Van Atteveldt, 2008). Entity extraction and linkage in AutoMap are computer-assisted processes. This means that the software applies a set of text pre-processing and link formation rules, which are defined by humans, and are also called a coding scheme (G. Ryan & Bernard, 2000). Section 5.2.2.1 provides more details on the steps needed for text coding in AutoMap.

In summary, the key piece needed not for only entity extraction, but also for text coding in general in AutoMap is a thesaurus. Section 5.2.2.1.1 reports in detail on preparing a thesaurus. For generating concept networks, a thesaurus needs to contain two columns: text terms on one side, and the associated concepts on the other side. For creating multi-mode network, an additional column is needed that associates concepts with entity classes. In AutoMap, concepts and entity classes can have attributes. There are no predefined or required types or sets of attributes. Similar to the creation of code books for content analysis, creating thesauri is a very time-consuming and cumbersome process, even if it is computer-supported, and requires people specifically trained for this task (Corman, et al., 2002; King & Lowe, 2003; Krippendorff, 2004; P. A. Schrodt, et al., 2008). Typically, thesauri need to be validated by assessing the degree to which one person assigns the same code to the same text over time (intra-coder reliability). We have added a plethora of features to AutoMap to make the thesaurus generation process more efficient, such as generating lists of terms and N-grams and their (weighted) frequencies, and stemming terms into their morphemes, which potentially allows for more hits per term (Diesner & Carley, 2004, 2008a).

3.2.2 Requirements for Entity Extractor

We identified a set of seven criteria as being important for an entity extractor that serves the purposes stated for this project in general and in AutoMap specifically. I began with specifying what type of network analysis the extracted entities data should support in the end. As introduced in section 0, different approaches to network analysis are suited for different purposes, and can be placed on a spectrum between social network analysis and network science. Table 50 summarizes key characteristics of these poles as they are relevant for this section, and provides examples of typical applications.

Table 50: Characteristics of Network Analysis approaches

Characte-ristic	Network Science	Social Network Analysis
Goal	- Identify, formally describe, model, and test hypothesis and advance theories about properties, dynamics and evolution of graphs, link data, and relational data.	- Answers substantial questions and advance theories about the individual and collective behavior and cognition of social agents. - Develop and test hypothesis and theories about implications and causes of the properties, dynamics and evolution of network data.
Research process (Figure 2)	- Focus on the computational analysis of data w.r.t. to a research question. Existing or benchmark datasets are often used.	- Data collection is often part of the analysis process.

Scalability	- Focus on large-scale graphs and change of graph properties as network sizes change.	- Traditionally, datasets, methods and tools were focus on network data of small to moderate size. This has shifted to ambitions to test and develop theories about networks of any size.
Exemplary application domains	- Technical infrastructures such as telecommunication networks and the internet (Barabási & Albert, 1999; Eagle & Pentland, 2006). - Other sizable socio-technical networks, e.g. geopolitical entities (Auerbach, 1913; Bass, 1969; MEJ Newman, Strogatz, & Watts, 2001; Simon, 1955). - Online social networks and social media data (Adamic & Huberman, 1999; J Leskovec, et al., 2007).	- In social sciences and organization science, mainly: - Innovation diffusion (Coleman, Katz, & Menzel, 1966; Kraut, Rice, Cool, & Fish, 1998) - Group structure and processes (Milgram, 1967; Sampson, 1968) - Communication networks (Monge & Contractor, 2003) - Learning and information processing of social agents (K.M. Carley & Palmquist, 1991; Collins & Loftus, 1975)

Ultimately, the goal with this project is to provide a technology that combines the advantages from both sides of the spectrum shown in Table 50. This means that I aim for a solution that extracts data which allows users to gain deep and rich knowledge about network of any size, to formally describe this knowledge, and to answer substantial questions about networks (Corman, et al., 2002; Hirst, 2006). I broke this high-level goal down into separate, more specific goals that are detailed in Table 51. These goals are relevant for this thesis, but are not a comprehensive list of requirement for network data collection tools.

Table 51: Goals for entity extractor

Goal	**What does the goal mean?**	**Why is the goal relevant in general?**	**How does it improve the status quo of AutoMap?**
1. Automation	The ability to automatically collect one-mode and multi-mode network data.	Contributes to scalability. Reduces time and labor costs. (Corman, et al., 2002)	Extracting networks in AutoMap requires the semi-automated construction and/or adaption of thesauri. This is very time-consuming and laborious (see section 5.2.2.1.1 for a description of thesaurus preparation).
2. Abstraction of terms to concepts or higher level aggregates	The ability to associate terms with higher level abstractions, e.g. concepts. In Entity Extraction, the entity classes are higher level	Enables analyses on different levels of granularity and aggregation. (Monge & Contractor, 2003)	The data structures used for network representation in AutoMap and ORA supports the association of terms with concepts (and attributes of) certain entity classes. Being able to efficiently extract these associations in AutoMap creates a more capable and efficient tool chain.

	aggregates.		
3. Generalization	The ability to identify new and unseen instances of entity classes and entity attributes.	Contributes to greater flexibility in extracting network data from new corpora. Reduces time and labor costs.	Automap is constrained to only find entities that are specified in a thesaurus. In order to also find and classify new terms, the thesaurus needs to be extended in a time-consuming, semi-automated way (see section 5.2.2.1.1 for details).
4. Support end-users in addressing substantial and meaning-ful questions about socio-technical networks	Being able to go from texts to network data to knowledge. Provide publicly available entity extractor that is readily useable.	Contributes to practical usefulness of network analysis. Allows for answering substantial questions about networks. (Alderson, 2008; D. Krackhardt & Carley, 1998)	ORA already supports the automated analysis of large-scale, multi-mode network data. Being able to efficiently extract this data with AutoMap creates a more capable and efficient tool chain.
5. N-gram detection	Correctly locate the boundaries of unigrams and multi-word entities.	Default requirement for NER. (Ratinov & Roth, 2009)	AutoMap provides a probabilistic solution for extracting unigrams only (Diesner & Carley, 2008a).
6. Allow terms to belong to multiple entity classes instead of just one	The same term can belong to multiple entity classes given a term's meaning and context. Such terms can be homonyms or identical terms.	Contributes to the disambiguation of homonymic terms. Prevents the loss of relevant information.	AutoMap can assign one term to one concept only, and one concept to one meta-network category only. This goal addresses the first step.
7. Entity Extraction (as opposed to focus on Named Entity Extraction)	Extract entities that are referred to by a name or not, which is particularly relevant for entity classes where many instances are not named.	Contributes to answering substantial questions about so-technical networks, e.g. about culture and ethnography. (Diesner & Carley, 2008a)	ORA supports the automated analysis of unnamed and unnamed entities. Being able to efficiently extract these entities with AutoMap creates a more capable and efficient tool chain.

3.2.3 Review and Selection of Method to Enable Automation, Abstraction, and Generalization

Achieving automation, abstraction and generalization (goals 1-3) requires the selection of an appropriate extraction method while keeping the subsequent use of entities for network construction in mind. I satisfy these three requirements by picking a method that best covers the stated goals: this method selection is based on my review of the main families of methods that

are available for generating concept networks from text data as summarized in (Table 52). Note that the focus of Table 52 is on methods for generating word networks, not methods for analyzing them. A more elaborated review of these methods is provided in Diesner and Carley (2010b), and of current computational methods also in Mihalca and Radev (2011). Some of the listed methods are outdated and hardly used anymore, but have laid the foundations for further advances. The semantic web, for instance, can be considered an extension of definitional semantic networks. Furthermore, some of the seminal methods overlap. Map analysis, for example, borrows elements from spreading activation theory and knowledge representation in artificial intelligence. Also, most of the listed methods were not developed with the goal of providing input to network analysis or to handle just the extraction of entities and relations, but rather for transforming texts into network presentations for solving tasks in specific application domains. I included those in this review not only to be comprehensive, but also to show that the construction of concept networks has roots in many disciplines.

Table 52: Review of family of methods for generating word networks

Families of methods for constructing word networks and seminal papers	**Automation** No: manual Yes: automated CoSu: computer supported	**Abstraction** No: use terms verbatim Yes: map terms to higher level representation	**Generali-zation** No: deterministic Yes: find new instances	**Steps needed to reason about meaning of network data**
1. Discourse Representation Theory (Kamp, 1981)	No	Yes	No	Data construction process
2. Mind maps (Buzan, 1974)	No, CoSo	Yes	No	Data construction process Data analysis
3. Concept maps (Novak & Gowin, 1984)	No, CoSo	Yes	No	Data construction process Data analysis
4. Hypertext (Trigg & Weiser, 1986)	CoSo	Yes	No	Network analysis Inference
5. Qualitative text coding according to Grounded Theory (Glaser & Strauss, 1967; T. Richards, 2002)	No, CoSo	Yes	No	Data construction process Data analysis

6. Mental Models according to Spreading Activation (Collins & Loftus, 1975; Collins & Quillian, 1969)	CoSo	No	No	Data analysis
7. Knowledge representation in artificial intelligence, assertional semantic networks (Shapiro, 1971; Woods, 1975)	Yes	No	No	Inference
8. Definitional semantic networks incl. networks built by using an ontology (Berners-Lee, et al., 2001; Fellbaum, 1998)	Generation: no Usage: yes	Yes	No	Data analysis Inference
9. Semantic Web (Berners-Lee, et al., 2001; Van Atteveldt, 2008)	Generation: no Usage: yes	Yes	No	Information retrieval
10. Case Grammar and Frame Semantics (C. Fillmore, 1982; C. J. Fillmore, 1968)	Generation: no Usage: yes	No	No	Data analysis
11. Frames (Minsky, 1974)	Generation: no Usage: yes	Yes	No	Data analysis
12. Semantic Grammars (Franzosi, 1989; C. W. Roberts, 1997a)	CoSo	Yes	No	Data analysis Statistical analysis
13. Semantic network in communication science (J. A. Danowski, 1993; Doerfel, 1998; van Cuilenburg, Kleinnijenhuis, & de Ridder, 1986)	CoSo, Yes	Yes	No	Network analysis
14. Centering Resonance Analysis (Corman, et al., 2002)	Yes	No	No	Network analysis
15. Map Analysis, Network Text Analysis in Social Science (K.M. Carley & Kaufer, 1993; K.M. Carley & Palmquist, 1991)	CoSo	Yes	No	Network snalysis
16. Event Coding in political science (King & Lowe, 2003; P. A. Schrodt, et al., 2008)	CoSo	Yes	No	Statistical analysis
17. Machine learning based on probabilistic graphical models (Howard, 1989; Pearl, 1988)	Generation: no (orig.) to yes Usage: yes	Yes	Yes	Inference Network analysis

In summary, the review suggests that machine learning methods that are based on probabilistic graphical models (PGM) (group 17) fulfill the requirements of automation, abstraction and generalization. Therefore, I selected this general type of a type for this project. The selection of a specific PGM-based method is described in section 3.3. However, this choice implies one limitation: in order to reason about the meaning of the extracted data, further network analysis is needed once the data have been constructed. This task is addressed in the next section.

3.2.4 Review and Selection of Approach to Support Addressing of Substantial and Meaningful Questions about Socio-Technical Networks

The fourth goal is the generation of data that allows for addressing substantial questions and reasoning about the meaning of networks. What does it mean for network data to support meaningful analysis? I discuss this question and conclude with the selection of an approach.

The meaning of relational representations of language and knowledge has been extensively discussed in the linguistics and artificial intelligence literature (Hirst, 2006; Ogden & Richards, 1923; Woods, 1975). There, concept networks that represent meaning are called semantic networks (for a brief synopsis see Diesner & Carley, 2011; J. Sowa, 1992; Woods, 1975). A unifying assumption across various approaches to semantic networks is that the meaning of concepts can be inferred from a concept's context as explicitly or implicitly provided in text data or the network data (Collins & Quillian, 1969; Griffiths, et al., 2007; Minsky, 1974; Shapiro, 1971; Weaver & Shannon, 1949). According to Hirst (2006), further progress in extracting meaning from texts will require a combined consideration of subjective authorial intent, subjective interpretations of the reader, and the extraction of objective representations of meaning from large-scale corpora.

In the network analysis literature, the meaning of word networks has hardly been discussed. There, the generally accepted assumption is that a node's meaning results from its context and the network position; both of which can be described by network analytical measures (K.M. Carley, 1997b; K.M. Carley & Kaufer, 1993; K.M. Carley & Palmquist, 1991; Doerfel, 1998; Mohr, 1998). Context here means the structural environment of a node, typically starting from the ego-network. Detecting a node's meaning basically requires completing the network analysis process as outlined in Figure 2. However, there is no guarantee that a concept network or its analysis will be meaningful. Moreover, it is easy to read patterns and meaning into networks, for example by making heuristic use of network visualizations (H. Bernard & Ryan, 1998).

A synthesis of prior work on enabling the reasoning about the meaning of word networks is provided in the last column of Table 52; suggesting that there are five options for achieving this goal: (1) some methods require humans to go through a cognitive, typically manual or computer-

supported, process of creating concept networks. This data construction process requires the representation of the meaning of concepts and relations as perceived by the people creating the data. With some of these methods, meaning can also be obtained by interpreting the resulting data. For example, when applying grounded theory methodology to construct structural models based on text data, the resulting data are assumed to be inherently meaningful, but require the analysts' interpretation with respect to a research question (Glaser & Strauss, 1967). In general, three types of analysis can be employed to get to the meaning of the data: (2) statistical analysis, (3) network analysis, and other types of (4) data analysis such as qualitative interpretations. Note that not all methods with which concept networks are generated assume the usage of network analysis methods to reason about the data. For example, semantic web data are generated to support information retrieval, and relational data generated with event data coding methods in political science are typically analyzed with non-relational statistical methods. Finally, some methods involve the possibility of conducting (5) inference on the generated data.

There are two more strategies for supporting the construction of meaningful data; both of which are an integral part of many of the outlined methods and cross-cut over the five strategies just outlined: First, concept networks can be constructed by using structured variables that are motivated by theory (Corman, et al., 2002; Van Atteveldt, 2008). Second, meaningful concept networks (in the sense of "semantic networks") can be generated by applying predefined classification schemata, i.e. specifications of the set of possible elements (ontologies) and relations between them (taxonomies) in a given domain (Berners-Lee, et al., 2001; Gerner, et al., 1994).

In order to ensure that the entity extractor built for this supports the construction of network data that allows for meaningful analysis, I combine the following elements which are all selected from the options discussed above:

1. Use an *ontology* that is grounded in theory from the social sciences and defines the entity classes that are typically relevant for representing socio-technical network (section 3.2.5).
2. Use *probabilistic graphical models* as the method for generating a prediction model that retrieves instances of these entity classes from text data (section 3.3).
3. Generate concept networks that are structured such that all entity classes, links between entities, and attributes of nodes and entities can be analyzed through *network analysis*, *statistical analysis* and *visualization* with an existing toolkit (ORA: Kathleen M. Carley, et al., 2011) This is demonstrated in chapter 5.

3.2.5 Selection of Ontology

The standard set of entity classes for Named Entity Recognition in NLP comprises *agents*, *organizations*, *locations* and miscellaneous *other* entities. In political science, the categories considered for event coding are *agents* and *events*, and for both of these categories, elaborated sets of subtypes exist, which are continuously updated in a collaborative fashion (P. A. Schrodt, et al., 2008). In organization science, Krackhardt and Carley (1998) have developed a multi-mode and multi-plex model called PCANS that defines the set of relevant entity classes; namely *agents*, *tasks* an *resources*. PCANS also specifies primitives or general templates for the possible relation between these classes. These primitives result from the logical and temporal ordering of activities, and can be represented as combinations of matrices of the considered entity types. Carley (2002a) has extended PCANS into the meta-matrix model in two ways: she further refined and extended the set of categories to represent the *who* (agent, organizations), *what* (task, event), *when* (time), *where* (location), *why* (emotions, beliefs) and *how* (resources, knowledge) of events. Also, she developed a plethora of network analytical measures that are defined over these nodes types. These measures are implemented in ORA (Kathleen M. Carley, et al., 2011). In general, most network analytical measures are defined independently of specific node types (Wasserman & Faust, 1994). Thus, these measures are assumed to be appropriate for analyzing networks of any type, including social networks and generic graphs. Tailoring measures to specific entity classes and types of networks as supported with the meta-matrix model and in ORA allows for more detailed and richer analysis. The meta-matrix model has been previously tested, applied and validated in a variety of contexts such as situational awareness in remote work teams (Weil, et al., 2008), collaboration in groups (Cataldo, et al., 2006), consumer markets (Feldstein & At, 2007), public health (Merrill, Bakken, Rockoff, Gebbie, & Carley, 2007), and geopolitical groups (K. M. Carley, et al., 2007). The definition of entity classes, attributes, subtypes of classes, and respective measures for the meta-matrix keeps being adjusted and updated.

In summary, I chose to use the meta-matrix model as an ontology for defining the entity classes that the entity extractor needs to recognize. This choice enables the collection of rich network data for which analytical measures have already been defined and validated, and for which an analysis tool is readily available.

3.2.6 Selection of Solutions to Entity Extraction, N-gram Detection, and Non-Exclusive Term Classification

Entity Extraction: The meta-matrix model comprises various categories in which entities are often not referred to by a name, such as tasks and resources. In the next step, training data needs

to be selected that contains examples a mix of named and unnamed entities for the entity classes of interest. The selection of an appropriate learning dataset is presented in section 3.3.1.

N-gram Detection: Each instance of a relevant entity class needs to be detected from its beginning to its end, whether it's a unigram or a multi-word expression. This is a token labeling task (S Sarawagi, 2008), which I herein refer to as boundary detection. In fact, with entity extraction via machine learning, every word in a text gets classified, but while only those matching entity classes are output in the end, the boundary label for each word is considered for accuracy assessment. In prior work, various classification schemas for boundaries have been used: the simplest one is BIO (begin, inside, outside), more advanced is BIEO (begin, inside, end, other), and even more detailed is BIEOU (begin, inside, end, other, unigram) (Ratinov & Roth, 2009; S Sarawagi, 2008). Choosing a model means making a tradeoff between expressiveness versus keeping the number of parameters for learning small. A model for a given project can be chosen by testing the performance of various models on the data, or by building upon prior empirical results. I chose the latter approach: Ratinov and Roth (2009) showed that BIEOU outperforms BIO by 0.5% to 1.3% on two training data sets, respectively. These datasets are similar in their genre and entity classes to the data that I use for learning. Currently, the entity extraction feature in AutoMap that was built by using a machine learning approach based on probabilistic graphical models is only capable of locating and classifying unigrams, regardless of whether they are constituents of N-grams or not (Diesner & Carley, 2008a). Adding a routine that properly handles multi-word expressions will help to improve the extraction of concept networks as well as meta-networks. Since concept networks are one-mode networks, the only applicable extracting entities task for these networks is boundary detection.

Allow terms to belong to multiple entity classes instead of just one: Ideally, entity extraction is a non-exhaustive, non-exclusive process. This means that not all words are relevant entities, but those that are relevant might fall into multiple categories depending on the terms' identity and context. What does that imply for the selection of a machine learning method? Since in fact most words in a text do not belong to one of the meta-network categories, the prediction model needs to be able to handle very sparse data. Sparse here means that most terms fall into the "O" (outside) category of the boundary coding schema. Thus, the methods must not strongly rely on transition probabilities of relevant entity classes, but needs to exploit other. Frequently used alternative clues are characteristics of the terms themselves, long-distance information in sequential data, and the relationship between a term and its label (A. McCallum, 2005; S Sarawagi, 2008). Currently, the way thesauri are processed in AutoMap requires that each term is mapped to only one concept, and each concept to only one meta-network category. Thus, our current thesauri are structured this way. Outputting thesauri where the same terms can be

mapped to multiple entity classes will enable the disambiguation of homonyms and identical terms that belong to different categories in different situations. Considering this modification to thesauri for actual text coding projects will require changes to the AutoMap backend that are not subject of the work for this thesis, but the outcome of this thesis is a precondition for this next move.

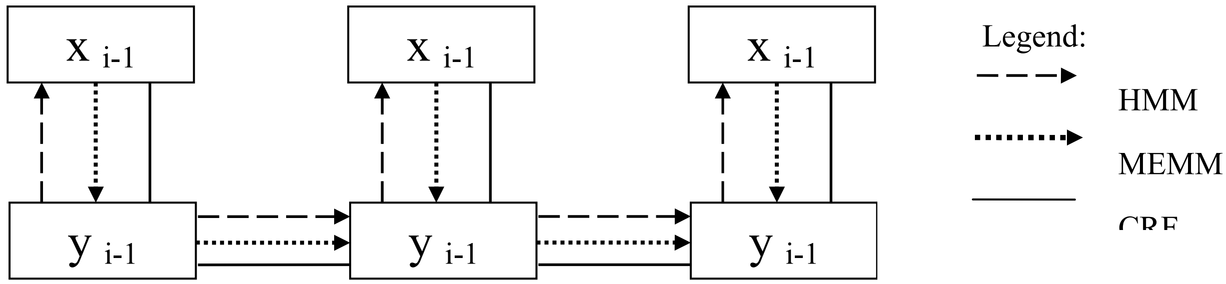
3.3 Method

Summarizing the findings from the requirements analysis, the following criteria were identified as being appropriate for an entity extraction method:

- A machine learning technique based on probabilistic graphical models (PGM).
- A technique that can handle the sparse distribution of relevant entities across text data.
- A technique that allows for assigning identical tokens to different categories. .
- A technique that is able to exploit long distance information in sequential data. Sequential here means that when generating text data, one does not draw terms and class labels independently from some distribution, and that terms and labels show sequential correlations. Due to the sequential nature of unstructured text data, a PGM is needed that is able to capture and exploit dependencies of tokens and labels (S Sarawagi, 2008).

Given the availability of suitable training data for the task at hand as described in section 3.3.1, I chose to use a supervised learning approach. In general, sequential supervised learning makes probabilistic predictions about the relationship between consecutive tokens x and a y label for every token (Dietterich, 2002). For this project, each token is an x, and the respective class label is the y. The learning goal for this project can be formulated as follows: Learn a prediction model, also known as a classifier, h that for each sequence of (x,y) suggests an entity sequence $y=h(x)$ that generalizes with predicable accuracy to new and unseen data. Several PGMs for sequential learning satisfy the identified requirements. I briefly describe eligible models along the dimensions of directionality and the type of distribution they estimate as these two characteristics are relevant for the given task. Figure 9 shows a schematic depiction of the PGMs discussed in this section.

Figure 9: Graph structure of selected Probabilistic Graphical Models



The directionality of the model represents assumed logical dependencies. In directed PGMs, every node is conditioned on its parent(s). In undirected models, distributions are factored into local likelihood functions for each clique of variables. PGMs can be divided into generative models and conditional models, aka discriminative models:

With generative models, a joint distribution of the form *P(x,y)* is estimated. An example for generative models that are frequently used for entity extraction are Hidden Markov Models (HMM). An early system that successfully used HMM for NER is IdentiFinder (D. Bikel, M. , et al., 1999) , which exploits multiple features of words and achieves a prediction accuracy 94.9%.

Conditional models estimate a conditional distribution of the form *P(y|x)*. For the given task, the output generated from conditional models, i.e. the most likely class label sequence *y* per token sequence *x*, is what we are interested in, while explaining how the token sequence was generated from the class labels through an assumed probabilistic process (generative models) is irrelevant. A highly accurately performing conditional PGM for NER are Conditional Random Fields (CRF) (Lafferty, McCallum, & Pereira, 2001; Sha & Pereira, 2003). CRF have shown to outperform alternative generative models. For instance, Lafferty et al. (2001) obtained an error rate of 5.55% with CRF, 6.37% with Maximum Entropy Markov Models (MEMM), and 5.69% with HMM. MEMM are another discriminative model (Borthwick, et al., 1998).

In general, the accuracy rates obtained with HMM are comparable to those achieved with conditional models. The main disadvantage with HMM are their strictly local properties: HMM lack the ability to directly pass information between non-adjacent *y* values (Dietterich, 2002). Also, each token is assumed to be generated from the corresponding class label only. Thus, information about other nearby labels cannot be considered. However, information about not directly co-located elements is particularly valuable when working with sparse data, and for multi-word units that are longer than two tokens. Conditional models do not have this limitation; they allow for the considering arbitrary features of *x*, including global and long-distance features (Dietterich 2002).

Within the group of conditional models, MEMM have led to higher error rates than generative models (Lafferty, et al., 2001). This limitation been explained with the "label bias problem": MEMM are a log-linear model that maximizes the conditional probability of each label y given the previous label y_{i-1} and the current token x_i. Once this is done, MEMM use maximum entropy to compute the highest conditional likelihood of all x: $\prod P(y_i| x_i)$. The label bias occurs in the first step: each y_{i-1} has to pass all of its probability mass to the adjacent label y_{i-1}, even if a token x_i hardly fits this choice (Lafferty, McCallum and Pereira 2001). Since CRF do not have the same local constraint, they can delay this decision until a good fit has been found.

CRF feature some additional advantages: First, they can find global optima in sequential data with respect to the target function specified for his project. Second, CRF can take arbitrarily large numbers of features into account. In fact, since the identity of every word can be used as a feature, the number of feature can easily be in the tens of thousands. This exceeds the handful of features typically used with more local modals by far. Therefore, more of the information available in text data can be exploited, including weak contributors, which are crucial for working with sparse data. Third, CRF allow for considering long-distance information between the tokens at least.

The main caveat with CRF is that they require high time costs for training. This is mainly due to performing global search with a reasonably sized gradient in a large feature space. However, once the model is learned, inference time is not subject to this constraint. Therefore, applying the model in end-user applications is fast and scalable.

In summary, given the outlined characteristics and strengths of CRF as well as the cited empiric results, I chose CRF as the PGM based machine learning technique for this project. This choice is supported by prior work: Sarawagi (2008) concludes that for data at the level of heterogeneity that we aim to provide an entity extractor for, i.e. mainly unstructured data from well defined genres and domains, conditional model and learning based on enough training data are the state of the art approach to this task. In our case, the domains to be covered are news coverage and other reports of interactions and events in organizations.

In contrast to HMM and MEMM, CRF model the relationship among each label y_i and its predecessor y_{i-1} as a Markov Random Field (MRF). MRF are an undirected PGM that is conditioned on x only. In CRF, the distribution $P(y|x)$ is computed as a normalized product of potential functions M_i, which are computed as shown in Equation 4 (Lafferty, et al., 2001; Sha & Pereira, 2003):

Equation 4

$$M_i(y_{i-1}, y_i \mid x) = (\exp\left(\sum_{\alpha} \lambda_\alpha f_\alpha (y_{i-1}, y_i, x) + \sum_{\beta} \mu_\beta g_\beta (y_i, x)\right)$$

In Equation 4, the f_α expression is an edge feature that represents the transitions between labels and tokens. Furthermore, g_β is a vertex feature that represents the emission of an entity from a term sequence. Feature vectors f_α and g_β are fixed, boolean vectors. Most of the time, a feature will be switched off or be zero (sparse data), and is turned on only when applicable. For example, the word identity feature, which our implementation includes, is only switched on when x contains that particular term. When a feature is switched on, the specific learned weight per feature, i.e. λ_α and μ_β, become applicable.

In order to normalize the scores of the potential functions, the M_i are typically multiplied with $1/Z(x)$. Here, Z is a normalizing constant parameterized on the sequence x. Finally, the conditional probability of the entire label sequence $P(y|x)$ is computed as shown in Equation 5. Note that in Equation 5, both, y and x are arbitrarily long vectors.

Equation 5

$$p_\theta(y \mid x) = \frac{\prod_{t=1}^{n+1} M_i(y_{i-1}, y_i \mid x)}{\prod_{i=1}^{n+1} M_i(x)_{start,stop}}$$

3.3.1 Learning Data

Supervised machine learning requires marked up or labeled data for training and testing. Since the goal here is to predict a boundary and category for every entity, a dataset is needed where the start, end and cagetory of all relevant entities are marked up. Building a high quality learning data set is expensive because it requires the training of humans for this task, a sufficiently high rate of intercoder reliability, and a sufficiently large number of marked up examples. No such dataset that covers instances of the meta-network categories has yet been created in our group. Therefore, I had to defer to external sources. In order to find the most suitable training data set for the task at hand, I reviewed the major datasets that are available to researchers for information extraction purposes. Table 5 provides a reference and a short overview of the main characteristics of these datasets. Some of these datasets cover the main set of entity classes that are typically considered in information extraction, but no further subtypes. These datasets are shown in Table 53, which also specifies how these main catgories are referred to in the meta-network model.

Table 53: Entity class review I: Models and datasets without subtypes

Entity class	Meta-network	ACE-2, TIDES	NYT	CoNLL-2003
Person	x (Agent)	x	x	x
Organization	x	x	x	x
Location	x	x	x	x
Facility	x (Location)	x		
GPE	x (Location)	x		

In some of these datasets, specific and generic instances of categories are not distinguished from each other. This would be problematic for the types of analysis we aim to support: in our practical work we often have seen that when identifying key agents in networks, generic nodes such as “president” often rank very high because they subsume references to multiple individuals, but are not as meaningful as the name of a specific president (Diesner & Carley, 2005b). This problem applies to references to roles of people and organizations in general. Therefore, datasets that allow for distinguishing between generic and specific entities are more appropriate here. The applicable datasets are compared in Table 54, which covers the same entity classes as Table 53 does. In addition to that, Table 54 lists the available subtypes per entity class and lines them up across corpora where possible.

The datasets considered in Table 54 go beyond the standard set of entity classes by providing markups for additional classes and their subtypes as shown in Table 55. The point of reference in Table 55 (leftmost column) is the set of categories defined for the meta-network model.

Table 54: Entity class review II: Models and datasets with subtypes

Entity class	MUC6, 7 (NE task)	Subtypes (IE task)	ACE 2004, 2005	Subtypes	BBN	Subtypes
Person	x	name alias title types (7): other, military, civilian	x	individual ('05) group ('05 indefinite ('05)	x	(name, desc)
Org.	x	name alias descriptor type: government, company, other	x	government commercial educational non-profit ('04) non-governmental ('05) religious ('05) media ('05) entertainment ('05) medical-science ('05) sports ('05) other ('04)	x	government (name, desc) corporation (name, desc) educational (name, desc) political (name, desc) religious (name, desc) hotel (name, desc) hospital (name, desc) museum (name, desc) other (name, desc)

Location	x	city province country region unknown water (7) airport (7)	x	address boundary celestial water body land region natural region local ('04) region sub-nat. ('04) region national ('04) region general ('05) region international other ('04)	x	border (name) lake sea ocean (name) river (name) region (name) continent (name) other (name)
Facility			x	airport ('05) plant building ('04) bldg. on grounds ('05) sub area building ('04) sub area facility ('05) bounded area ('04) conduit ('04) path barrier ('04) other ('04)	x	airport (name, desc) building (name, desc) bridge (name, desc) highway street (name, desc) attraction (name, desc) other (name, desc)
GPE			x	continent nation state or provine county or district city or town ('04) population center ('05) GPE cluster ('05) special ('05), other	x	country (name, desc) state province (name, desc.) city (name, desc) other (name, desc)

Table 55: Entity class review III: Additional entity types

Meta-network entity class	MUC6, MUC7 (NE task)	Subtypes (IE task)	ACE 2004, ACE 2005 (*= value of entry)	Subtypes	BBN	Subtypes
Resource	Artifact (IE task)	ID, description type (7): air, ground, water	Vehicle	air, land, water, subarea vehicle, other ('04), underspec. ('05)	Product	weapon (name, desc) vehicle (name, desc) other (name, desc)
			Weapon	blunt, exploding, sharp, chemical, biological, Nuclear, other ('04), underspec. ('05)	Substance	food, drug, nuclear, chemical, other
					Plant Animal Disease	
	Money		Money ('05)*		Money	
Time	Time	7: descriptor,	Time ('05)*	TIMEX2, incl.:	Time	

	Date	start, end type: before, on, after, between		present, past, future type: within, start, end, as of, before, after	Date	date, duration, age, other
Knowledge					Law Language Work of art	(name) (name) book (name) play (name) song (name) painting (name) other (name)
					NORP	nationality (name) religion (name) political (name) other (name)
			Contact ('05)*	email, phone#, URL	Contact info	address, phone #, other
Belief						
Attributes	Percent -	- -	Percent ('05)*		Percent Ordinal Cardinal Quantity	 1D, 2D, 3D, energy, speed, temperature, weight, other

This comparison shows that no dataset covers all of the meta-network categories, but BBN comes closest to that by covering all but the "beliefs" category. However, in BBN, one subtype of agents and organizations is "religious", which captures the notion of agents adhering to a belief. This label approximates the purpose behind the belief class in the meta-network.

Table 56 furthermore compares the various additional attributes or classifications that the reviewed datasets provide per each entity. In BBN, the generic versus specific distinction as well as further subtypes of entity classes (if applicable) are directly encoded in the category label itself, while in MUC and ACE, any additional information is marked up as separate attributes per entity. In general, BBN integrates features from different datasets: similar to ACE, it annotates numerous subtypes of entities. Like MUC, is separates all entities into named entities, temporal expressions and numerical expressions.

Table 56: Entity class Review IV: Additional attributes for entities

Meta-network	**MUC6, MUC7 (NE task)**	**ACE 2004, ACE 2005**	**BBN**	**ACE-2, TIDES**
For Per, Org, Loc:	For each entity:			
specific	named entity	name	named entity	name

generic		nominal pronoun		nominal pronoun
		for each entity (2nd attribute):		for each entity (2nd attribute):
	temporal ex- pression number ex- pression	negatively quantified non-ref./attribut./ascriptive specific referential generic referential under-specified referential	temporal ex- pression number ex- pression	generic specific

The only entity class that is treated differently in the discussed learning datasets than in the meta-network model is the activities category: in the meta-network model, instances of the "task" and "events" class comprise a single word or a short phrase, such as "participate in". Nodes of these types can be linked to any type of entities. A similar approach to event coding is typically taken in political science, where events are terms that can have a valence value and take agents as their arguments (Gerner, et al., 1994; Goldstein, 1992; King & Lowe, 2003; P. A. Schrodt, et al., 2008). There, the types of events and agents are predefined, while specific instances of these entity classes are identified from the actual text data. The goal with this type of event coding is to identify who does what to whom.

In contrast to that, in NLP-style information extraction, event coding is conceptualized as a slot filling or relation extraction task: an event or scenario consists of various entities of predefined types that play certain, predefined roles or have certain relationships with each other. These events are typically very specific and cannot be expected to generalize well to other types of activities. Table 57 compares the event coding approaches in the potential learning datasets. This comparison shows that the ACE 2005 data encodes a variety of events that are relevant for asking substantial questions about socio-technical networks. Moreover, ACE 2005 offers predefined valence values (polarity) for these events. BBN lacks these features, but offers a different advantage: event mark-ups in BBN are most close to the way that the meta-network model represents activities. However, the types of events considered in BBN are confined to specific wars, hurricanes and other events as well as games, such as sports games.

Table 57: Event coding review

Meta Net-	**MUC6, MUC7 (NE task)**	**ACE 2005**	**Subtypes**	**BBN**	**Subtypes**
Event	6: management succession: succession in and out	life movement transaction	be born, mary, divorce, injure, die transport transfer ownership	Event	war (name) hurricane (name) other (name)
Task			transfer money	Game	
		business	start org, merge org, end org,		
	7: air vehicle launches:		declare bankruptcy		

	launch event	conflict	attack, demonstrate	
	vehicle info	contact	meet, phone, write	
	payload info	personnel	start position, end position, nominate, elect	
		justice	arrest jail, release parole, trial hearing, charge indict, sue, convict, sentence, fine, execute, acquit, appeal, pardon	
		arguments:	who, when, where, instrument, price, target	
		values:	crime, sentence, job title	
		Per event:		
		polarity (occurred or not)		
		tense (past, presence, future)		
		genericity (generic, specific)		
		modality (asserted, other)		

In summary, the review of potential learning datasets suggest that with respect to types and subtypes of entity classes, the distinction between generic versus specific examples, and the consideration of events, ACE 2005 and BBN would be appropriate datasets for the given task. In order to decide for one of them, I compared the number of entities per category as shown in Table 58. This is a relevant criterion because learning requires a substantial amount of examples per category. Note that in ACE, pronouns are also marked up as entities, and comprise about 14% of all annotated entities. This is very useful for reference resolution tasks, but for this project, I do not aim to classify pronouns as entities. Disregarding pronouns, BBN contains more than twelve times the number of entities that ACE offers. Therefore, I chose to use BBN as learning data for this project.

Table 58: Quantitative comparison of suitable learning datasets

Category	ACE 2005	Number of Examples	BBN	Number of Examples
Agent	name	1,123	name	13,750
	nominal	2,111	descriptor	26,352
	pronoun	1,143		
	Subtotal (no pronoun)	3,234	Subtotal	40,102
Organization	name	887	name	19,450
	nominal	729	descriptor	30,244
	pronoun	182		
	Subtotal (no pronoun)	1,616	Subtotal	49,694
Location	name	127	name	1,088
	nominal	182		
	pronoun	24		
	Subtotal (no pronoun)	309	Subtotal	1,088

Facility	name	56	name	445
	nominal	343	nominal	2,570
	pronoun	45		
	Subtotal (no pronoun)	399	Subtotal	3,015
GPE	name	2,622	name	13,571
	nominal	527	nominal	1,835
	pronoun	382		
	Subtotal (no pronoun)	3,149	Subtotal	15,406
Vehicle	name	28	name	382
	nominal	183	nominal	1,223
	pronoun	27		
	Subtotal (no pronoun)	211	Subtotal	1,605
Weapon	name	15	name	21
	nominal	262	nominal	132
	pronoun	27		
	Subtotal (no pronoun)	277	Subtotal	153
Time		1,235		1,069
Money		94		11,097
Percent		17		5,976
Contact Info		2		40
Events	7 subtypes	1,557	3 subtypes	371
			Game	90
	Subtotal	1,557	Subtotal	461
Distinct classes	Values (3 subtypes)	165	Other named entities	9,448
			Other numerical entities	12,047
			Other temporal entities	20,676
Total	With Pronouns	14,094		
	Without Pronouns	**12,318**		**171,877**

Next, the categories in BBN had to be mapped to the meta-network categories. Table 59 shows the outcome of this process. I picked one best match per category by reviewing the descriptions in the BBN documentation, screening the examples in BBN (last column in Table 59) and in existing CASOS thesauri, and making sure that no category has too few examples (second column from the right in Table 59). The only category that I did not map onto a meta-network equivalent is "contact info: address", since a) this category has no good match in the meta-network, and b) there are only four examples; two of which are overlapping with the class of "location: street".

Table 59: Category mapping from training data to category models

BBN	**Mapping of BBN to Meta-Network**				**Example from BBN**
Category name	**Category name**	**Subtype I**	**Subtype II**	**Examples /group**	
per_desc	agent	generic	na	26,352	activist
person	agent	specific	na	13,750	Arafat

org_desc:corporation	organization	generic	corporate	15,186	advertisers
org_desc:educational	organization	generic	educational	238	high school
org_desc:government	organization	generic	governmental	2,502	administration
org_desc:hospital	organization	generic	other		clinic
org_desc:hotel	organization	generic	other		hotel-casino
org_desc:museum	organization	generic	other		institution
org_desc:other	organization	generic	other	1,322	bar
org_desc:political	organization	generic	political	151	campaign
org_desc:religious	organization	generic	religious	51	church
organization:corporation	organization	specific	corporate	23,439	Occidental Petroleum Corp.
organization:educational	organization	specific	educational	366	Carnegie Mellon University
organization:government	organization	specific	governmental	4,629	Bank of Japan
organization:hospital	organization	specific	other		Harlem Hospital Center
organization:hotel	organization	specific	other		Ritz
organization:museum	organization	specific	other		Smithsonian Institute
organization:other	organization	specific	other	1,353	American Bar Association
organization:political	organization	specific	political	413	African National Congress
organization:religious	organization	specific	religious	44	Church of Scientology
norp:religion	org-att	specific	religious	88	Jewish
norp:nationality	org-att	specific	nationality	3,238	African
norp:other	org-att	specific	other	91	African-Americans
norp:political	org-att	specific	political	677	Communist
fac:airport	location	specific	facility		Heathrow
fac:attraction	location	specific	facility		Angel Fire
fac:bridge	location	specific	facility		Bay Bridge
fac:building	location	specific	facility		Andre Emmerich Gallery
fac:highway_street	location	specific	facility		101
fac:other	location	specific	facility	445	Auschwitz
fac_desc:airport	location	generic	facility		airport
fac_desc:attraction	location	generic	facility		aquarium
fac_desc:bridge	location	generic	facility		bridges
fac_desc:building	location	generic	facility		apartments
fac_desc:highway_street	location	generic	facility		circle
fac_desc:other	location	generic	facility	2,570	courtyard
gpe:city	location	specific	city	5,606	New York City
gpe:country	location	specific	country	5,079	Angola
gpe:other	location	specific	other		Bronx
gpe:state_province	location	specific	state-province	2,694	Alaska
gpe_desc:city	location	generic	city	377	capital
gpe_desc:country	location	generic	country	992	empire
gpe_desc:other	location	generic	other		borough
gpe_desc:state_province	location	generic	state-province	397	Baden-Wuerttemberg
location:border	location	specific	other		Four Corners
location:continent	location	specific	other		Africa
location:lake_sea_ocean	location	specific	other		Baltic Sea
location:other	location	specific	other		Alps
location:region	location	specific	other		Allegheny Mountains
location:river	location	specific	other	1,349	Amazon
animal	resource	na	animal	396	black widow

disease	resource	na	disease	317	cardiac condition
plant	resource	na	plant	194	cotton
product:other	resource	specific	product		Budweiser
product:vehicle	resource	specific	product		400 series
product:weapon	resource	specific	product	923	AH-64 Apache
product_desc:other	resource	generic	product		lifeboat
product_desc:vehicle	resource	generic	product		ambulance
product_desc:weapon	resource	generic	product	1,381	machine guns
substance:chemical	resource	na	substance		acid
substance:drug	resource	na	substance		cocaine
substance:food	resource	na	substance		bourbon
substance:nuclear	resource	na	substance		plutonium
substance:other	resource	na	substance	2,714	antibody
money	resource	na	money	11,097	$17
language	knowledge	specific	language	84	Arabic
law	knowledge	specific	law	382	425 U.S. 308
work_of_art:book	knowledge	specific	art		1984
work_of_art:other	knowledge	specific	art		60 Minutes
work_of_art:painting	knowledge	specific	art		Cemetery in the Snow
work_of_art:play	knowledge	specific	art		Death of a Salesman
work_of_art:song	knowledge	specific	art	721	I Can See Clearly Now
event:hurricane	event	specific	na		Hugo
event:other	event	specific	na		Big One
event:war	event	specific	na	371	French revolution
game	task	na	game	90	basketball
date:date	time	na	na		31-Mar-94
date:duration	time	na	na		10-month-long
date:other	time	na	na		annual
time	time	na	na	21,125	1 p.m. EST
cardinal	attribute	na	numerical		1.97
ordinal	attribute	na	numerical		200th
percent	attribute	na	numerical		0.30%
quantity:1d	attribute	na	numerical		1.2 miles
quantity:2d	attribute	na	numerical		8.2 by 11.7 inches
quantity:3d	attribute	na	numerical		1.6-liter
quantity:energy	attribute	na	numerical		900 megawatts
quantity:other	attribute	na	numerical		32-bit
quantity:speed	attribute	na	numerical		200 mph
quantity:temperature	attribute	na	numerical		321 degrees Fahrenheit
contact_info: other	attribute	na	numerical		ENG 23
Contact_info: phone	attribute	na	numerical		900-TELELAW
quantity:weight	attribute	na	numerical	18,059	2.5-ton
date:age	attribute	na	age	620	33

The BBN dataset had a few XML consistency issues that I fixed: four categories were defined in the BBN specification for which there were no examples in the annotated data. Eleven categories were not defined for BBN, but occurred in the annotated data with a total of 19 examples. I went through each of the examples and changed the category to what it should be according to the

BBN documentation and the actual examples. One entity started as one type and ending as a different type; I adjusted that. Another issue with the data resulted from the fact that in XML data in general, a forward slash within an entity closes an XML tag prematurely. To avoid this issue, BBN places a forward slash right after a backward slash where applicable. This happens mainly for cardinal numbers, such as “1\/4 to 1\/2”, and organization, such as “Capital Cities\/ABC Inc.” However, a backward slash followed by forward slash is highly unlikely to be observed in new data. Therefore, I converted this structure into just a forward slash after parsing the XML files and prior to passing the input data to the learner.

3.3.2 Learning Technology and Selection of Feature Types

As a starting point for implementing the entity extractor, I used the CRF package as provided on the CRF project package (Sunita Sarawagi). This package offers a basic implementation of CRF, is highly adjustable, and allows for adding new features. The next challenge is to find a robust set of clues, also known as features, which bring together information about different characteristics of the data such that accuracy becomes high while predictions are robust. Robust here means that we need to avoid overfitting of the learned models to the idiosyncrasies of the learning data in order to ensure that the learner generalizes with high accuracy to new inference data. However, even though the feature set that will be chosen at the end of the feature selection process needs to support robustness, individuals features can be weak (S Sarawagi, 2008).

Prior work has shown that in general, the following types of features are useful for entity extraction tasks: the identity of a token, i.e. the actual word or phrase, word surface features, orthographic features, syntax features, and external knowledge (D. Bikel, M. , et al., 1999; Borthwick, et al., 1998; Cohen & Sarawagi, 2004; Florian, et al., 2003; Mayfield, McNamee, & Piatko, 2003; Andrew McCallum & Li, 2003). In the following discussing of these features, I distinguish between “feature types” versus “features”, which are individual different clues per feature type.

3.3.2.1 Input Decomposition and Class Definition

Entity Extraction can be approached as a sequence labeling or a token labeling task. Token labeling means that for each individual word, two labels need to be predicted: 1) a boundary class label and 2) an entity class label or category. For example, for the entity “United Nations”, the predicted labels might be “begin, organization, specific” for “United”, and “end, organization, specific” for “Nations”. This task can be solved via one joint model for boundary and category, or two separate models for each label type. The advantage with the first approach is that there can be no conflicts between both label types. The disadvantage is that in the respective PGM, the number of classes, also known as states, and edges between states is would

be higher than with the second approach. As a result, fewer examples per class are available from the same training data. Furthermore, the higher complexity of the model leads to a higher time complexity for training. The advantages with the second approach are the higher number of examples per class, which also implies lower time requirements for learning. Furthermore, the features for boundary prediction and class label prediction can be tuned separately. The caveat is that both labels per token need to be combined in the end, which is highly likely to cause further loss in accuracy due to disagreements between both models.

With sequence labeling, one label gets predicted for each sequence, which can be a unigram or a multi-word expression. The same advantage and disadvantages as described above for the joint model of boundary and category prediction exist. Considering the outlined pros and cons, I chose to use the token labeling approach that predicts the boundary and category per token separately for the following reasons:

The entity extractor built here is meant to support users in extracting two types of networks: one-mode networks, where all nodes are of the same type, and multi-mode networks, where nodes are instances of the meta-network categories. In order to extract nodes for one-mode networks, it is sufficient to correctly locate entities within their boundaries, but without assigning them to an entity class. Adding the detection of unigrams and bigrams as a stand-alone functionality to AutoMap would eliminate the need to identify these entities with alternative, computer supported techniques that require further manual vetting and selection (see section 5.2.2.1 for a description of how this is currently handled in AutoMap). This can be achieved with a prediction model that performs boundary detection only, which is the first reason for why I decided to construct a separate boundary prediction model. Next, in order to provide nodes for the construction of multi-modal networks, any located entities need further to be classified. This requires a second model for category prediction. In this process, however, nodes still need to be located as well. In order to keep the locating of nodes for one-mode networks and multi-mode networks in sync for the entity extraction method in general and for AutoMap in particular, I decided to use the same boundary prediction model for both situations, and to combine the boundary model with a class prediction model for building multi-mode networks (for details on combining both models see section 3.4.4).

Given the selected training data and the meta-network model, category labeling for this project can be based on four different category label models. These models are shown in Table 60. All of these models adhere to the meta-network ontology, but differ in the amount of granularity that they encoded in the entities (for details on the specific entity classes in each model see Table 59). Theoretically, entity class model 4, which is the most complex or detailed one as it specifies the meta-network category, specificity and subtype of each entity, can be reduced to each of the

other entity class models. However, due to the model complexity and thus the lower number of training instances per category, the model might not perform as well as the simpler ones. This would mean a loss of accuracy or practical usefulness for the end-user. The same argument can be made for reducing entity class models 2 (category and specificity) and 3 (category and subtype) to entity class model 1 (category only). My assumption here is that higher complexity leads to lower accuracy. I am report on the outcome of testing this hypothesis in the results section. The choice for a specific model has another aspect to it: for practical purposes, different data sets and research questions might require different levels of detail such that we cannot anticipate which model would be most useful. Thus, each of the models could be suitable for text coding in AutoMap, and would expand the current scope of capabilities of this tool. Thus, we decided to generate all four options, and to report on their accuracy and robustness so that users can pick the model that best serves their needs; potentially trading off accuracy for granularity.

Table 60: Entity class model definition

	Category name (meta-network classes)	**Subtype I (generic vs. specific)**	**Subtype II (attributes per class)**	**Example**
Entity class model 1	x			agent
Entity class model 2	x	x		agent, specific
Entity class model 3	x		x	agent, political
Entity class model 4	x	x	x	agent, specific, political

Table 61 reports on the complexity of the token labeling approaches (separate versus joint models for boundary and category) and the class label models in terms of the number of classes and edges and run time. These tests were performed by learning with 80% of the data (4 holdout folds) and making predictions on the remaining 20% of the data (1 holdout fold) for two different, but not all five holdout folds, and averaging the results. A more complete description of the evaluation routine is provided in section 3.4.1. Each of the tested holdout folds has about 43,000 labeled tokens. The runtime was measured with the baseline feature set that is explained in section 3.3.2.2. The time needed for a single iteration of the CRF varies greatly depending on the model complexity[10]: for boundary detection, it is only one minute, while for joint prediction of boundary and category with entity class model 4, it is 175 minutes. As reported in section 3.4.4 in more detail, 300 iterations is a rate at which results start to stabilize. This rate would require over a month of runtime for the most complex model for the joint prediction option. However, during the feature testing and selection stage, it is crucial to test the contribution of

[10] All experiments described in this chapter were run on a total of three different machines with 64 bit operating systems. One machine had 256 GB of RAM and 24 processors, the other two machines had 512 GB of RAM and 64 processors.

each feature type to accuracy separately, to then modify or drop features accordingly, and to repeat this process as often as necessary. The token level approach, especially one that breaks boundary and category prediction into separate tasks, supports this need better than the alternative approach. This fact is the second reason for why I chose the token level approach that involves a model for boundary and category prediction each. However, I present extraction results for both token labeling approaches with a low iteration rate in order to clarify on the difference in accuracy.

Table 61: Token labeling approaches: complexity per model*

Token labeling approach	**Size and Runtime costs**	**Boundary Model**	**Entity class model 1**	**Entity class model 2**	**Entity class model 3**	**Entity class model 4**
Separate models for boundary and class	Number of States Number of Edges Runtime: Min. per iteration Runtime for 300 iterations	5 25 1 5 hours	11 121 3.5 17.5	16 256 6 1.25 days	32 1,024 15 3.1 days	45 2,025 24 5 days
Joint model for boundary and class	Number of States Number of Edges Runtime: Min. per iteration Runtime for 300 iterations	n.a.	41 1,681 17 3.5 days	60 3,600 31 6.5 days	121 14,641 126 26.3 days	155 24,025 175 36.5 days

*holdout folds 1,3, number of states and edges for sequence level from holdout fold 3

3.3.2.2 Baseline Features

The CRF project package contains various feature types. The following eight features are the ones that I considered as being potentially relevant for establishing a baseline for this project:

1. *Word Features:* Identity per token.
2. *Word Score Features:* The log of the number of tokens with a certain label over the number of all tokens with that label.
3. *Edge Features*: Information about transitions between states.
4. *Start Features:* Active when current state is a start state.
5. *End Features:* Activate when current state is an end state.
6. *Unknown Feature:* Active for token not observed during training.
7. *Known In Other State Feature:* Active when a token was not observed in a particular state, but in other states with more than a minimum threshold frequency.
8. *Regex Features*: A collection of multiple orthographic characteristics and regular expressions per token.

All of these features are implemented on a per state basis, except for the first feature, which is implemented on per token level. Overall, these features represent common features for

information extraction tasks that are solved via machine learning methods, especially those that use PGM with Markov properties (D. Bikel, M. , et al., 1999; Diesner & Carley, 2008b; Ratinov & Roth, 2009). This particularly applies to the edge features, the start and end features, and the unknown feature.

3.3.2.3 Syntax Features

In order to identify the part of speech (POS) for each token, I use the POS tagger that I had previously built for AutoMap (Diesner & Carley, 2008b). This tagger implements a HMM via the Vitberi algorithm, operates on the sentence level, and tags every sequence of characters that is composed of any combination of letters, numbers, dashes, ampersands, dollar symbols, and single hyphens. The latter mainly serves as genitive markers. Any token that does not match this pattern is disregarded for tagging, including hyphens composed of two single hyphens. The tagger achieves an accuracy of over 93% on predicting two different tag sets: the Penn Treebank (PTB) tag set with 36 tags, and a set where the PTB tags are aggregated into more general tags, such as all verb forms to “verb” (for the mapping from PTB to the aggregated tag set see the Appendix in Diesner & Carley, 2008b). I refer to these tag sets as “full” and “aggregated”, respectively, in the following.

Using the tagger for this project revealed two issues: First, the tagger predicts two categories that do occur in the training data that the tagger was built based upon, i.e. PTB 3 (P. M. Mitchell, Santorini, & Marcinkiewicz, 1993), but that are not defined for the full PTB tagset. Specifically, the tag “JJSS” should rather be “JJS”, and “PRP$R” should be “PRP$P”. This problem was noted by others before (Pereira, 2004), but was not spotted when building the AutoMap POS tagger. In order to find out if this glitch matters, I mapped the two undefined categories onto the ones they truly should be and tested the impact on the entity extraction accuracy. The results as shown in Table 62 suggest that this ex post factum fix hurts prediction accuracy, mainly by lowering recall. This is because in the POS training data, the undefined tags were assigned to one different term each, such that the resulting tagger would put these words into separate classes of their own. In order to keep the entity extractor in sync with AutoMap, which uses the POS tagger that contains the additional two categories, I decided to not to keep this change for further work on this project. Ultimately, this issue can be solved by retraining the tagger.

Table 62: Impact of Parts of Speech tag fix on accuracy*

	Boundary Prediction		**Class Prediction**	
	original	fixed	original	fixed
Precision	88.1%	88.4%	85.7%	85.7%
Recall	85.7%	85.1%	81.2%	81.0%
F	**86.9%**	**86.7%**	**83.4%**	**83.3%**

*Iteration Rate 200, Class model 1

Second, when I screened the results of POS tagging of the tokens in BBN, I realized that most tagging errors applied to numbers, especially percentages, which were wrongfully assigned to classes other than the numbers class. However, in the BBN data, most of the tokens that involve digits truly are numbers. Thus, I made another ex post factum change to the POS tagger: any token that contains a digit is tagged as a number, i.e. as "CD" for the PTB full set, and as "NUM" for the aggregated set. I kept this change for learning.

Parts of speech can be used as a feature for CRF as a) a per state feature, or b) a per state and per word feature. Which of these two options and which of the two available POS tag sets achieve higher accuracy rates is shown in the results section.

3.3.2.4 Lexical Features

Prior research has shown that the accuracy of entity extraction can be increased by adding features that use external knowledge sources such as a lookup dictionary (Brown, Desouza, Mercer, Pietra, & Lai, 1992; R Bunescu, et al., 2005; Cohen & Sarawagi, 2004; Ratinov & Roth, 2009). In fact, several of the potential trainings sets discussed in this chapter include gazetteer data as additional files. Using dictionaries has also been shown to help with domain adaption, i.e. adapting an extractor from the training data domain to other domains for conducting inference (Ciaramita & Altun, 2005).

For this project, I use the thesaurus that I prepared as described in detail in section 5.2.2.1.1 as a dictionary. This thesaurus contains 169,791 entries and is herein referred to as the "master thesaurus". The left hand side of the thesaurus contains potential text level entries, and the right hand side has the related meta-network category. Of those entries, 59.6% are locations. However, this category includes plenty of noisy entries, which mainly result from scraping the web without careful cleaning the retrieved hits, and adding stemmed versions and foreign translations of location to the thesaurus; some of which might be valid English words that would rather belong into different meta-network categories. Both of these routines were performed by others before I took over work on the master thesaurus. I fixed many of those issues as described in section 5.2.2.1.1. However, I neither removed the translations nor locations that were unknown to me, but sounded like valid entries. Since runtime costs increase with the size of the thesaurus, but many of these location entries are unlikely to occur in new text data, I built a reduced version of the master thesaurus as follows: I took out all locations (169,791 entries) and replaced them with just the names of all countries and capitals in the world (439 entries) as provided in (Research, 2011). The resulting thesaurus contains a total of 69,067 entries and is 59.3 % smaller than the original master thesaurus. I refer to this thesaurus as the "reduced master thesaurus".

Building upon prior work and extending it with new lexical features, I added the following lexical features to the CRF implementation:

1. *Is in Dictionary Feature:* Activated if token matches complete content of left hand side entry in thesaurus. Executed on the unigram level. Implemented per state. This feature is motivated by (Ciaramita & Altun, 2005).
2. *Is in Dictionary per Word Feature:* Same as above, but implemented per state and per word.
3. *Occurs in Dictionary Feature:* More relaxed version of the “Is in Dictionary Feature”. Activated if token matches any part of the content of left hand side entry in thesaurus. Matches on token level among unigrams and within N-grams are valid. Implemented per state. This feature is motivated by Cohen and Sarawagi (2004).
4. *Position in Dictionary Feature:* If token occurs in dictionary, this feature records the position of a token in the left hand side entry of the thesaurus. Matches among unigrams and within n-grams are valid. Positions available are begin, inside, end, and unique. Example: if the token is “House” and the thesaurus contains “White House”, then “House = end” gets recorded. Implemented per state. This feature is motivated by Cohen and Sarawagi (2004).
5. *Position in Dictionary per Word Feature:* Same as above, but implemented per state and per word.
6. *Category Feature:* If token occurs in left hand side entry of thesaurus, this feature records the meta-network category of that token. Matches among unigrams and within n-grams are valid. Implemented per state.
7. *Category per Word Feature:* Same as above, but implemented per state and word.

Cohen and Sarawagi (2004) have shown that using soft matches instead of exact matches of tokens to dictionary entries further increases accuracy. However, the thesauri I use already contain grammatical and lexical variations of words, including inflexions, conjugations, morphemes, abbreviations, and synonyms. Further computing string similarities between text tokens and the dictionary entries might enable the consideration of more token variants than those already provided in the thesauri, but might also pick up on false positives. Moreover, computing string distance metrics adds significant time costs to the learning process, especially for dictionaries as large as the ones used here. For the given reasons, I only consider hard matches between text tokens and dictionary entries, but compute a variety of dictionary features that aim to capture different characteristics of the thesaurus entries.

3.3.3 Experimental Design

Table 63 gives an overview on the feature types or variables that need to be tested for their individual and combined contribution to extraction quality. This table also specifies the variables' value ranges that I consider potentially useful for this project. Testing all combinations of the values of the selected feature types would result in an 8*9*2*5*2*2*2*7 = 40,320 design. Doing these experiments would be an overkill for this project because not all combinations are meaningful, and many of them can be ruled out once the best value for a specific variable has been identified. Thus, I mainly conduct experiments to identify the best value per parameter, and then incrementally combine them across parameters.

Table 63: Experimental design: variables and values

Variable	Values								
Baseline	Word Features	Word Score Feature	Edge Features	Start Features	End Features	Un-known Feature	Known in other state Fea.	Regex Features	
Iteration Rate	100	200	300	400	500	600	700	800	900
Token Labeling	Separate models for boundary and class	Joint model for boundary and class							
Class label model	Boundary Model	Entity class model 1	Entity class model 2	Entity class model 3	Entity class model 4				
Syntax Features	PTB full	PTB aggregated							
	POS per state	POS per word							
Lexical Features	Full master thesaurus	Reduced master thesaurus							
	Is in Dictionary Feature	Is in Dictionary per Word Feature	Occurs in Dictionary Feature	Position in Dictionary Feature	Position in Dictionary per Word Feature	Category Feature	Category per Word Feature		

3.4 Results

3.4.1 Evaluation Method and Metrics

The accuracy rates presented in this section were obtained by performing k-fold cross validations: I split up the BBN data into five chunks, also known as folds, of about equal size. The folds are static, i.e. the same files stay in the same bucket for all experiments. For each run, all folds expect for the holdout folds are used for training a prediction model. During evaluation, the learned model is applied to the holdout fold, and each deviation from the original tag per token in the holdout fold (ground truth) is recorded as an error. At the end of all runs per experiments, where the number of runs equals k, the obtained accuracy rates are averaged. No

fold is ever used for training and evaluation in the same run. Ideally, one would iterate through each of the five folds as being the holdout fold once per experimental condition (5-k cross validation). This strategy is used for assessing the accuracy of the final models. Practically, the experiments were constrained by the computing resources that were available to me and the time costs for experiments. Therefore, I use a reduced approach for assessing the accuracy rates for the values per variable: I perform two runs per experimental condition with two randomly selected holdout sets, which were folds 1 and 3.

3.4.2 Points of Comparison for Accuracy Rates

To the best of our knowledge, no other group has used BBN to predict the meta-matrix categories specifically. Therefore, I have no precise external point of comparison for the accuracy rates that will be obtained. However, results from the main Named Entity Extraction initiatives are applicable points of comparison: in ConLL 2003, the Named Entity task involved extracting the boundary and category labels for the classes of person, organization and location. The top five systems achieved F-measures of 85% and more; with the best system having an F value of 88.7% (CoNLL-2003, 2003; Florian, et al., 2003). In MUC7, the categories to predict were more similar to BBN that those used in CoNLL 2003, and in fact, BBN data was part of this task (for details see Table 54 and Table 55). The top two systems in MUC7 achieved F-values of 91.6% and 94.4%, and four more systems had F-values of more than 85% (MUC7, 2001). The goal with this project is not to beat these benchmark values, but to stay in the range of state of the art performance values by using cutting edge methods and technologies, and also leveraging on routines (e.g. POS tagging) and material (e.g. lookup dictionary) that I have developed for AutoMap and CASOS. These routines and materials are an integral part of current tools and research projects that we have developed and conducted, respectively.

Previously, we have applied CRF to BBN to train a model that predicts a class label per token with an accuracy rate of 82.7% (Diesner & Carley, 2008a). This model differs from the ones build in this project in the following ways: First, it only operates on the unigram level, i.e. multi-word expressions are not retrieved as such. In other words, no boundary detection is performed. Second, it uses entity class model 1, i.e. meta-network categories only without further attributes. Third, it considers a smaller number of the categories available in BBN (details on the mapping of BBN categories to meta-network categories are provided in Table 1 in (Diesner & Carley, 2008a). The goal with this project is to improve on this baseline in multiple ways: first, to extract unigrams as well as N-grams. Second, to extract entities that adhere to more complex entity class models. Third, to capture attributes per entities. And finally, to improve the accuracy rate.

3.4.3 Baseline

As the results in Table 64 show, six of the eight baseline feature types contribute to accuracy. The "known in other state" feature has no impact. The "word score" feature reduces accuracy by a few percentage points. The ranking of how much the feature types impact accuracy is the same for the three most useful feature types for both, boundary and category prediction. The "word identity" feature is by far the strongest clue. Information about transitions is also greatly helpful. From this point on, the features that are not contributing to accuracy are excluded from the feature set such that the baseline consists of six feature types.

Table 64: Accuracy loss due to elimination of each single baseline feature*

Boundary	**All Baseline Features**	**Word**	**Edge**	**Regex**	**Start**	**End**	**Un-known**	**Other State**	**Word Score**
Precision Recall F	84.5% 83.7% 84.1%	-28.3% -38.5% -34.0%	-19.9% -24.5% -22.3%	-2.9% -6.0% -4.5%	-0.3% -1.6% -1.0%	0.0% -2.0% -1.0%	-0.1% -2.7% -1.4%	0.0% 0.0% 0.0%	3.9% 3.2% 3.5%
Rank (based on F, 1=best)		1	2	3	5	6	4	no con-tributor	no con-tributor
Class	**All Baseline Features**	**Word**	**Edge**	**Regex**	**Start**	**End**	**Un-known**	**Other State**	**Word Score**
Precision Recall F	84.8% 82.3% 83.5%	-31.1% -46.9% -41.3%	-10.5% -11.9% -11.3%	-3.6% -2.3% -2.9%	-0.1% -0.7% -0.4%	-1.7% -2.2% -2.0%	-1.0% 0.1% -0.4%	0.0% 0.0% 0.0%	2.6% 1.9% 2.2%
Rank (based on F, 1=best)		1	2	3	5	4	6	no con-tributor	no con-tributor

*Iteration rate = 300, class model 2, holdout folds: 1,3, Class

3.4.4 Iteration Rate and Input Decomposition

Increasing the number of iterations leads to substantial gains in accuracy up to an iteration rate of about 500, where gains start to become minimal, as shown in Table 64. In Table 64, the last horizontal row in each section shoes the change rate in F as the iteration rate is increased by 100. Accuracy starts to drop from about 700 iterations on. Precision is higher than recall and benefits less form increasing the iteration rate than recall does, though this effect decrease as the iteration rate is increased.

Figure 10 illustrates this effect for a particular holdout set: the number of tokens retrieved and tokens correctly classified increases approximately by the same amount per iteration rate. For practical purposes, however, recall is more important than precision as retrieved yet misclassified entities (false positives) might be suitable fits for alternative categories. Overall, the results

support the strategy of using an iteration rate of 300 for further testing of the impact of features since the results are fairly robust at this point.

Table 65: Impact of iteration rate on accuracy*

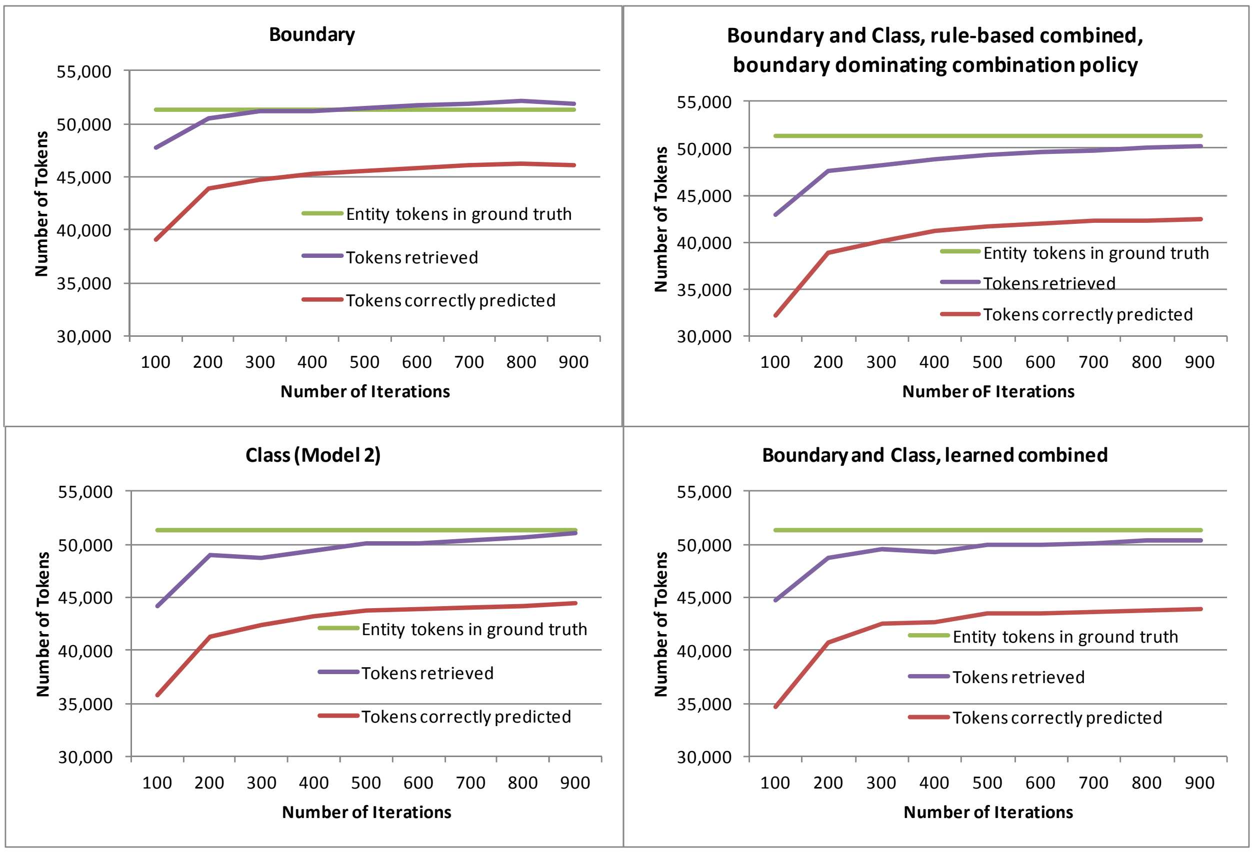
	Iteration Rate								
Boundary	**100**	**200**	**300**	**400**	**500**	**600**	**700**	**800**	**900**
Precision	82.8%	87.3%	88.4%	89.0%	89.1%	89.3%	89.4%	89.6%	89.5%
Recall	77.6%	85.3%	86.9%	88.1%	88.9%	89.3%	89.6%	89.6%	89.9%
F	80.1%	86.3%	87.6%	88.5%	89.0%	89.3%	89.5%	89.6%	89.7%
Change Rate in F		6.2%	1.3%	0.9%	0.5%	0.3%	0.3%	0.0%	0.1%
Class (Model 2)									
Precision	82.4%	86.0%	87.9%	88.4%	88.4%	88.6%	88.5%	88.4%	88.2%
Recall	70.0%	80.6%	82.9%	84.3%	85.1%	85.6%	86.1%	86.3%	86.6%
F	75.7%	83.2%	85.3%	86.3%	86.7%	87.1%	87.2%	87.3%	87.4%
Change Rate in F		7.5%	2.2%	0.9%	0.4%	0.4%	0.1%	0.1%	0.1%
Boundary & Class	Rule-based combination of separately learned models, boundary dominates class								
Precision	76.4%	82.7%	84.4%	85.1%	85.3%	85.6%	85.5%	85.5%	85.3%
Recall	63.6%	75.8%	78.5%	80.2%	81.3%	81.9%	82.4%	82.3%	82.8%
F	69.4%	79.1%	81.3%	82.6%	83.2%	83.7%	83.9%	83.9%	84.0%
Change Rate in F		9.7%	2.3%	1.3%	0.6%	0.5%	0.2%	0.0%	0.2%
Boundary & Class	Rule-based combination of separately learned models, class dominates boundary								
Precision	75.3%	79.3%	82.0%	82.7%	82.7%	83.0%	83.0%	83.0%	82.7%
Recall	64.0%	74.3%	77.4%	78.9%	79.6%	80.2%	80.7%	81.0%	81.2%
F	69.2%	76.7%	79.6%	80.8%	81.2%	81.6%	81.8%	82.0%	81.9%
Change Rate in F		7.5%	2.9%	1.1%	0.4%	0.5%	0.2%	0.1%	0.0%
Boundary & Class	Learned joint model								
Precision	78.3%	84.5%	86.7%	87.8%	88.1%	88.2%	88.0%	88.1%	88.2%
Recall	67.1%	79.2%	82.6%	83.4%	84.9%	84.9%	85.5%	85.7%	85.9%
F	72.3%	81.8%	84.6%	85.6%	86.5%	86.5%	86.7%	86.9%	87.0%
Change Rate in F		9.5%	2.8%	1.0%	0.9%	0.0%	0.2%	0.2%	-0.6%

* Holdout folds 1,3

With respect to the results for input decomposition, the results in Table 65 suggest that when separate models are learned for boundary and category prediction, boundary prediction is over 2% more accurate than category prediction. This seems intuitive since the boundary model contains less than half the number of labels than the entity class model (in this case Nr. 2) does. Learning a joint model for boundary and category prediction (last horizontal section in Table 65) is slightly less accurate than learning separate models for both types of prediction prior to consolidating them. This difference becomes smaller as the iteration rate increases; at 500 iterations it is 2.5% and 0.2% in comparison to boundary prediction and class prediction, respectively. However, when separate models are learned for boundary and category prediction, these models need to be merged in the end, and accuracy assessment needs to be performed

again on the joint models. My results show that either approach of merging as explained right below leads to accuracy rates that are about 3% and more less accurate than those obtained with the joint model. However, I argue that learning boundaries and category labels with separate models leads to more robust final models because there is much more training data available for each class. Also, learning the joint model took four times as long (10.8 days at 500 iterations) than the separate models did (2.1 days). Since we aim for high generalizability of the models, I chose to stick with this more robust solution.

Figure 10: Diminishing returns: Impact of iteration rate on accuracy*



* Class model 2, holdout fold 1

The decision to work with separately learned models for boundary and category prediction implies that once both types of models have been generated, they need to be combined before inference can happen. This combination needs to be done such that we obtain a) both, a boundary label and a class label, for each token and b) consistent labels, especially for multi-word units. Table 66 provides an overview on the discrepancies that that can occur.

I developed and implemented a rule based approach for combining these models and resolving any discrepancies between them by considering all logically possible mismatches and suggesting

a solution for each of them, and using a data driven approach for checking the learned baseline models for the characteristics of these discrepancies and testing the impact of any suggested solution. The outcome of this process, i.e. the resulting rule set, is shown in Table 66. The developed rule set is based on two different policies for handling mismatches between boundary and class labels: 1) boundary prediction dominates class prediction, and 2) class prediction dominates boundary prediction:

Boundary prediction dominates category prediction: If there is a class label but no boundary label with the value of begin, inside or end, the token is not considered as an entity. If the class labels in a multi-word unit according to boundary prediction are not coherent, I assign the most frequent label (other than none) to all tokens in that expression. In the case of a tie, the first category is picked. For cases in which boundary prediction finds a unigram but no class label is suggested, I tested two strategies: not considering the token as a relevant entity al together, or assigning the token to the most frequent class label. My error analysis of the outcome suggested that the errors fall with almost equal frequency into three categories: 1) being a token of the type of the most frequent type of entity class, 2) being a token of some other type of entity class, or 3) being a false positive according to boundary prediction. Case 2 occurred slightly more frequently than case one. Therefore, I chose to assign no class label to unigrams that lack a class label and converting these entities to the “outside” boundary condition.

Category prediction dominates boundary prediction: If a token has a class label other than none, but the token right before and after do not, and the boundary label for this token is outside or part of a multi-word unit, the boundary label is set to “unigram”. If the sequencing of boundary labels does not coincide with a multi-word unit according to class label prediction, the boundary labels are adjusted accordingly. Note that with this policy, mismatching unigrams are preserved, while with the first policy, they are lost, which gives the second policy a potential advantage over the first one.

Testing both policies empirically suggests that letting the using the policy where the boundary label dominates the category label returns slightly more accurate results (1% and less). This finding seems intuitive because boundary prediction is overall more accurate than class label prediction. Cases in which the category dominating policy preserved unigrams led to significant ratios of truly false hits, which diminished the potential gains from this strategy.

The rule-based procedure described in this section was only used for accuracy assessment throughout the results section of this chapter. For integrating the entity extractor into an end-user software product, a more permissive approach was chosen in order to allow for higher recall. This approach is explained in section 4.

Table 66: Rules for model combination depending on combination policy

Policy	Case	Learned Labels		Combination Result	
Boundary dominates Category		Boundary	Class	Boundary	Class
	1	none	positive token (i.e. category not none)	none	none
	2	unigram	none	none	none
	3	N-gram	all tokens none	none	none
		N-gram	different category labels, at least one positive token	N-gram as learned	majority class label other than none, ties broken alphabetically
Category dominates Boundary	4	unigram	none	none	none
	5	none, begin, inside, end	positive token	unigram	positive token as learned
	6	inconsistent with class label sequence, incl. one to all boundary labels equal none	positive N-gram	proper N-gram	positive N-gram as learned

These and many other results for the impact of individual feature type values on accuracy were obtained by averaging the outcomes of cross-validations with holdout sets 1 and 3. In order to verify that these two folds are not outliers, which would impact the drawn conclusions and subsequent modeling decisions, I present a snapshot of sample sizes, number of features, and accuracy rates for all holdout sets for a constant iteration rate in Table 68. These numbers show that basically all five folds are similar in size, and lead to similar accuracy rates; with a variation in F of about 0.4% for boundary prediction and 1.6% for class prediction. Also note that the number of features is between 50,000 and 51,250 for class prediction, and between 53,500 and 54,500 for boundary prediction. This means that with only six baseline feature types, a large number of features is generated; with most of them being word features. This also means that for boundary prediction, which involves 5 states and 25 edges, more features are generated than for class prediction, which has 16 states and 256 edges for this entity class model. The reason for this counterintuitive effect is that with fewer classes, the learning data is less sparse such that more useful features might be found.

Table 67: Size and accuracy per holdout set at constant iteration rate

Measures	Holdout Set: 1	2	3	4	5
	Boundary				
Number of Entity Tokens	43380	43467	42937	43078	43652
Number of Features	54122	54204	53607	53737	54455
Precision	86.9%	87.3%	87.7%	87.8%	87.4%
Recall	85.4%	85.6%	85.2%	85.4%	85.3%
F	86.2%	86.4%	86.4%	86.6%	86.3%

	Class (Model 2)				
Number of Entity Tokens	43380	43467	42937	43078	43652
Number of Features	50824	50944	50355	50476	51252
Precision	84.4%	86.7%	87.6%	87.6%	86.8%
Recall	80.5%	79.9%	80.7%	80.2%	80.2%
F	82.4%	83.1%	84.0%	83.7%	83.4%

*Iteration rate = 200, holdout folds: 1,3

3.4.5 Syntax Features and Entity Class Models

In general, most features can be implemented on a a) per state or b) per word and state basis. Table 68 shows a comparison of these two options for the parts of speech tags feature type. The per state approach leads to a slightly higher accuracy (less than 1%) with less than half the number of features generated, i.e. the per state option is more efficient and more robust. Therefore, this option is used for further work.

Table 68: Impact of Parts of Speech tag feature implementation approach on accuracy*

POS Feature Implementation		Boundary		Class	
	Iteration Rate	200	400	200	400
Per State	Precision	88.1%	89.3%	85.7%	88.4%
	Recall	85.7%	88.4%	82.1%	84.8%
	F	**86.9%**	**88.9%**	**83.8%**	**86.6%**
Per Word and State	Precision	87.7%	88.8%	86.5%	88.4%
	Recall	85.1%	88.1%	80.0%	84.5%
	F	**86.4%**	**88.5%**	**83.1%**	**86.4%**

* holdout folds: 1,3, Class model 2

The results for the impact of using parts of speech as a feature type (Table 69) suggest that both, the aggregated as well as the full tag set, have a small positive impact on accuracy rates. The full tag set leads to higher gains in accuracy over the baseline than the aggregated set does for boundary detection and all entity class models except for model 4, where the results for both tag set tie.

Table 69: Impact of Parts of Speech tag features and entity class models (models sorted by accuracy) on accuracy*

Assessment Metrics	**BL**	**POS Agg**	**POS Full**
	Boundary		
Precision	88.4%	89.1%	89.1%
Recall	86.9%	86.5%	87.5%
F	87.6%	87.8%	88.3%
Change in F from Baseline (BL) to POS		**0.2%**	**0.7%**
	Entity class model 2 (meta network category + gen/spec)		

Precision	87.9%	86.9%	87.0%
Recall	82.9%	83.7%	84.3%
F	85.3%	85.3%	85.6%
Change in F from BL to POS		**-0.1%**	**0.2%**
Diff. in F over next less accurate class model	**1.3%**		**0.6%**
	Entity class model 1 (meta network category)		
Precision	85.5%	86.5%	86.5%
Recall	82.6%	82.8%	83.5%
F	84.0%	84.6%	85.0%
Change in F from BL to POS		**0.6%**	**1.0%**
Diff. in F over next less accurate class model	**1.0%**		**1.4%**
	Entity class model 4 (meta nw. cat. + gen/spec + subtype)		
Precision	85.3%	85.5%	85.1%
Recall	80.9%	81.9%	82.1%
F	83.0%	83.6%	83.6%
Change in F from BL to POS		**0.6%**	**0.6%**
Diff. in F over next less accurate class model	**0.9%**		**0.5%**
	Entity class model 3 (meta network category)		
Precision	83.5%	84.4%	84.6%
Recall	80.9%	81.2%	81.5%
F	82.2%	82.8%	83.1%
Change in F from BL to POS		**0.6%**	**0.9%**

* Iteration rate = 300, holdout folds: 1,3

With respect to entity labeling according to the four different entity class models as defined in Table 60, the results in Table 69 indicate that accuracy rates do not necessarily drop as the complexity of the models, i.e. the number of states and edges, increases. In fact, the second smallest model (entity class model 2, category and specificity), performs best. Also, the most complex model (model 4, category, specificity, subtype) outperforms model 3 (category, subtype). Moreover, the accuracy differences between the entity class models are fairly small (2.5% for the widest gap after POS tagging), even though the model complexities are very different (the number of classes differ by a factor of about 4 between the largest and the smallest entity class model). Based on these results I reject my hypothesis that greater model complexity leads to lower accuracy rates.

3.4.6 Lexical Features

Adding lexical or dictionary features boost accuracy by up to 4% (Table 70). However, only four of the seven dictionary features defined and tested for this project have a robust, positive impact on accuracy across dictionaries (full versus reduced master thesaurus) and prediction models (boundary versus category). These are the "Is in Dictionary per Word Feature (by far the strongest feature), Category Feature, Category per Word Feature, and Position in Dictionary per

Word Feature. The Position in Dictionary Feature returns the exact same results as the Is in Dictionary Feature. The same is true for the Position in Dictionary Feature per Word and the Category Feature. Therefore, both Position in Dictionary features are excluded from here on.

For most of the tested conditions, using the full master thesaurus as a dictionary leads to slightly better results than the using the reduced master thesaurus (0.4% on average for the selected dictionary features). However, the full master contains more than twice as many entries as the reduced one does, but hardly leads to more than twice as much accuracy gain. Therefore, I chose to use the reduced master thesaurus as well as the Is in Dictionary per Word Feature, Category Feature, and the Category per Word Feature for further work.

Table 70: Impact of dictionaries and dictionary features on accuracy

Features	Baseline	Is in Dictionary	Is in Dict. per Word	Category Feature	Category per Word	Occurs in Dictionary
	Boundary, Reduced Master Thesaurus					
Precision	88.4%	88.6%	92.1%	88.5%	88.5%	88.5%
Recall	86.9%	87.2%	90.6%	87.5%	87.3%	86.6%
F	87.6%	87.9%	91.3%	88.0%	87.9%	87.5%
Difference to BL**		0.31%	**3.71%**	**0.42%**	**0.32%**	-0.10%
	Boundary, Full Master Thesaurus					
Precision	88.4%	89.0%	92.1%	88.9%	88.6%	88.5%
Recall	86.9%	86.7%	91.1%	87.9%	87.7%	87.0%
F	87.6%	87.8%	91.6%	88.4%	88.2%	87.7%
Difference to BL**		0.22%	**3.98%**	**0.80%**	**0.56%**	0.12%
	Class (Model 2), Reduced Master Thesaurus					
Precision	87.9%	87.3%	91.1%	88.0%	87.8%	88.0%
Recall	82.9%	82.6%	86.3%	84.0%	83.4%	82.5%
F	85.3%	84.9%	88.6%	85.9%	85.5%	85.1%
Difference to BL**		-0.48%	**3.27%**	**0.56%**	**0.18%**	-0.21%
	Class (Model 2), Full Master Thesaurus					
Precision	87.9%	87.6%	91.4%	87.7%	87.8%	87.8%
Recall	82.9%	82.7%	87.3%	84.0%	84.1%	82.5%
F	85.3%	85.1%	89.3%	85.8%	85.9%	85.1%
Difference to BL**		-0.27%	**3.92%**	**0.49%**	**0.54%**	-0.28%

* Iteration rate = 300, holdout folds: 1,3

** Bold if gain over BL for both holdout folds

3.4.7 Final Feature Set

Based on the presented results from the tests of the impact of iteration rate, input decomposition, syntax features and lexical features, the feature set shown in Table 71 was used for constructing the model to be integrated into AutoMap.

Table 71: Final feature set for prediction models (active feature types in black, feature types not chosen in gray)

<table>
<tr><th>Variable</th><th colspan="9">Values</th></tr>
<tr><td>Baseline</td><td>Word Features</td><td>Word Score Feature</td><td>Edge Features</td><td>Start Features</td><td>End Features</td><td>Un-known Feature</td><td>Known in other state Fea.</td><td>Regex Features</td></tr>
<tr><td>Iteration Rate</td><td>100</td><td>200</td><td>300</td><td>400</td><td>500</td><td>600</td><td>700</td><td>800</td><td>900</td></tr>
<tr><td>Decom-position</td><td>Token Level</td><td>Sequence Level</td></tr>
<tr><td>Class label model</td><td>Boundary Model</td><td>Entity class model 1</td><td>Entity class model 2</td><td>Entity class model 3</td><td>Entity class model 4</td></tr>
<tr><td rowspan="2">Syntax Features</td><td>PTB full</td><td>PTB aggregated</td></tr>
<tr><td>POS per state</td><td>POS per word</td></tr>
<tr><td rowspan="2">Lexical Features</td><td>Full master thesaurus</td><td>Reduced master thesaurus</td></tr>
<tr><td>Is in Dictionary Feature</td><td>Is in Dictionary per Word Feature</td><td>Occurs in Dictionary Feature</td><td>Position in Dictionary Feature</td><td>Position in Dictionary per Word Feature</td><td>Category Feature</td><td>Category per Word Feature</td></tr>
</table>

For these experiments, a 5-fold cross-validation was conducted. The results in Table 72 show the accuracy rates for the entity class models with the final feature type configuration. Overall, the performance of the combined boundary and class label models is very similar across the different class label models; with 1.4% difference at most. This indicates that large differences in model complexity have little impact on accuracy. The results also confirm the previously identified ranking of models based on accuracy, with the least complex model being outperformed by the next complex model, and the most complex model being more accurate than the next less complex one. Moreover, the obtained results (accuracy between 87.5% and 88.8% for the combined models) are comparable to alternative top performing systems, where accuracy rates typically range in the 80ies and lower 90ies (see for example Florian, et al., 2003; MUC7, 2001). Furthermore, the achieved rates are 6% to 7% higher than the ones achieved with the previous entity extractor in AutoMap, which used a less complex category model (Diesner & Carley, 2008a).

Table 72: Final accuracy results per model

	Boundary Model	**Entity class model 1 (meta-network category)**	**Entity class model 2 (meta-nw cat. + specificity)**	**Entity class model 3 (meta-nw cat. + subtype)**	**Entity class model 4 (meta-nw cat. + specificity + subtype)**
Precision	93.2%	91.4%	91.9%	90.4%	90.8%
Recall	92.5%	89.7%	90.0%	88.6%	88.9%
F	92.9%	90.6%	90.9%	89.5%	89.8%

	Bound. & Class combined, rule-based	Entity class model 1	Entity class model 2	Entity class model 3	Entity class model 4
Precision	n.a.	89.7%	90.0%	88.6%	88.9%
Recall		87.7%	87.7%	86.4%	86.5%
F		88.7%	88.8%	87.5%	87.7%

The remainder of this results section provides error analyses for the boundary model and each entity class model[11]. I decided to conduct these error analyses on the level of individual models, not the level of merged boundary and category models, in order to enable the scrutinizing of each component individually before they are fused. Also, since the combination rules used for accuracy assessment (rigorous) are not same as the ones for integrating the models into end-user software (more forgiving about false positives, details in 4), this component-wise error analysis is more insightful. For error analysis of the boundary model, I kept the outside tag in the analysis, which is a rigorous and comprehensive approach, while for the category models, I exclude the "none" category tag. The reason for this decision is that the "none" category accounts for 76.6% of all tokens in each model, which diminishes the ratio of the relevant entity classes in the ground truth, but this ratio is an important piece of information in the error analysis. However, for the previously presented assessments, the outside and none labels were treated the same as any other label since they can (and here actually do) subsume false negatives from other categories, and can produce false positives[12] and false negatives[13] themselves, which impacts the overall accuracy rate.

Several trends can be observed across all models: Differences between accuracy per class within models are much greater than differences in overall accuracy rates across models (Table 72). Within models, high accuracy is not a matter of class size (measured as the ratio of tokens in a class over the number of tokens in the corpus). This means that small as well as large classes can achieve high accuracies. Here, high means around and above the overall accuracy for a model as shown in Table 72, and low means rates below of that.). However, the inverse of this effect is not

[11] For the boundary model and entity class models 1 and 2 I show the confusion matrices of errors in this section, for entity class models 3 and 4 those matrices are placed in the Appendix as they are very space consuming. The tables with the statistical results for the error analysis per model all share the same structure and are shown in this section. The tables and figures contain a "na" for logically not applicable attributes.

[12] False positives are entities that were detected as members of a particular class, but truly are members of a different class. Those entities are false alarms (negative interpretation) or additional, weaker suggestions that sometimes save entities from being lost to the "none" class in case they are assigned to some alternative class (positive interpretation).

[13] False negatives are entities that were not detected as members of a particular class, but actually are members of that class. Those entities are missed entries for a class.

true: low accuracy rates are only obtained for small classes (excluding the "none" label for categories). In fact, for all accuracy rates below 84.5%, the size of the impacted classes is less than 2% each, and the total size of the impacted classes is less than 10% of the corpus (again, excluding the "none" label).

Table 73: Error analysis, boundary model (absolute values)

	Prediction					
Ground Truth	unigram	unigram	unigram	unigram	unigram	Sum
unigram	99,384	852	203	1,091	8,802	110,332
begin	1,049	56,964	1,461	56	2,011	61,541
inside	234	1,816	36,412	1,111	2,325	41,898
end	1,218	25	1,127	58,003	1,168	61,541
outside	5,782	1,684	1,840	1,080	890,182	900,568
Sum	107,667	61,341	41,043	61,341	904,488	1,175,880

Table 74: Error analysis, boundary model (ordered by natural sequence of an expression)

Boundary Label	Accuracy	False negatives	False positives	Ratio of size	Tokens in ground truth	Correct tokens	False negatives	False positives
unigram	90.1%	9.9%	7.7%	40.1%	110,332	99,384	10,948	8,283
begin	92.6%	7.4%	7.1%	22.4%	61,541	56,964	4,577	4,377
inside	86.9%	13.1%	11.3%	15.2%	41,898	36,412	5,486	4,631
end	94.3%	5.7%	5.4%	22.4%	61,541	58,003	3,538	3,338
outside	98.8%	1.2%	1.6%	76.6%	900,568	890,182	10,386	14,306

The more detailed the entity class models are, the larger is the number of low-performing classes. These results support my strategy of consolidating small classes prior to learning. A similar trend can be observed for the ratio of false positives and false negatives: for most of the highly accurate classes, the ratio of false positives is higher than the ratio of false negatives, while this trend flips over for low performing classes. For practical purposes, both error types are most detrimental when false negatives are assigned to the "outside" or "none" class. This is because for the integrating the models into a software available to end users as described in section 4, all other types of error are preserved and explicitly marked. The results do not suggest any apparent relationship between class accuracy rates and the amount of false negatives that the "outside" or "none" label account for per class, and the ratio of these two labels among the false negatives can be anywhere between very small and very large.

Table 75: Error analysis, entity class model 1 (absolute values)

	Prediction											
Ground Truth	**agent**	**attribute**	**event**	**knowledge**	**location**	**none**	**organization**	**org-att**	**resource**	**task**	**time**	**Sum**
agent	45,346	10	21	103	367	2,541	988	48	80		24	49,528
attribute	7	29,847		12	7	1,581	27		208		396	32,085
event	26		533	45	13	69	21	1	4		39	751
knowledge	309	25	5	1,721	111	629	274	20	46		54	3,194
location	665	37	2	89	20,269	1,600	923	10	58		23	23,676
none	990	1,557	24	483	717	889,025	3,217	34	1,379	22	3,120	900,568
organization	2,417	76	3	296	1,205	5,298	71,623	50	150		54	81,172
org-att	116	2		14	43	79	82	4,058	12		4	4,410
resource	286	301	6	128	87	2,678	310	10	34,268		72	38,146
task	10					66	5			17		98
time	23	614	5	28	5	2,178	17	9	18	1	39,354	42,252
Sum	50,195	32,469	599	2,919	22,824	905,744	77,487	4,240	36,223	40	43,140	1,175,880

Table 76: Error analysis, entity class model 1 (sorted by decreasing accuracy)

Entity Class	Accu-racy	False Nega-tives	False Posi-tives	Size of cat. in ground truth	Tokens in cat.	Accu-rate pre-dictions	False Nega-tives	False Posi-tives
time	93.1%	6.9%	8.8%	15.3%	42,252	39,354	2,898	3,786
attribute	93.0%	7.0%	8.1%	11.7%	32,085	29,847	2,238	2,622
org-att	92.0%	8.0%	4.3%	1.6%	4,410	4,058	352	182
agent	91.6%	8.4%	9.7%	18.0%	49,528	45,346	4,182	4,849
resource	89.8%	10.2%	5.4%	13.9%	38,146	34,268	3,878	1,955
organization	88.2%	11.8%	7.6%	29.5%	81,172	71,623	9,549	5,864
location	85.6%	14.4%	11.2%	8.6%	23,676	20,269	3,407	2,555
event	71.0%	29.0%	11.0%	0.3%	751	533	218	66
knowledge	53.9%	46.1%	41.0%	1.2%	3,194	1,721	1,473	1,198
task	17.3%	82.7%	57.5%	0.0%	98	17	81	23

Across the various entity class models, we generally obtain very high accuracy rates (in the 90ies) for the categories agent, attribute and time, high rates (upper 80ies) for organizations, locations and resources, medium rates (70ies) for events, and low rates (50ies and less) for knowledge and tasks. Regardless of the model, all variations of task and knowledge are consistently ranking lowest. For locations, specific instances are predicted with higher accuracy than generic ones, and vice versa for resources.

Table 77: Error analysis, entity class model 2 (absolute values)

	Predictions																
Ground Truth	agent gen.	agent spec.	attribute na	event spec.	knowledge spec.	location gen.	location spec.	none	org. gen.	org. spec.	org-att spec.	resource gen.	resource na	resource spec.	task na	time na	Sum
agent gen.	25,221	56	6	5	28	17	33	2,151	349	96	14	5	20	4		8	28,013
agent spec.	19	19,646	5	12	137	1	482	441	6	610	15		18	101		22	21,515
attribute na	1	3	29,890	1	13	3	7	1,626	1	21			101	17		401	32,085
event spec.		19	1	540	45		19	67	1	23	3		1	1		31	751
knowledge spec.	23	183	37	8	1,750		138	648	2	295	16		21	28		45	3,194
location gen.	22	2			2	3,256	15	981	117	15			14			5	4,429
location spec.	12	388	40	2	93	18	17,456	579	4	583	15		16	22		19	19,247
none	636	207	1,486	27	571	426	343	889,749	1,021	1,668	34	204	1,041	50	30	3,075	900,568
org. gen.	462	3	14		13	93	6	1,259	17,677	70	2	10	4			3	19,616
org. spec.	104	1,214	63	7	392	1	1,111	4,014	75	54,313	59	1	40	117		45	61,556
org-att spec.	49	18	8		21		55	105	1	74	4,063		5	7		4	4,410
resource gen.	1	1	1		3	2	2	345	27	5		1,002	2	2		4	1,397
resource na	20	27	215		21	27	21	2,021	10	38	16		32,996	32		39	35,483
resource spec.	14	104	97	4	139		85	170	3	226	4	1	29	356		34	1,266
task na	1	1			2		1	61		3					29		98
time na	5	11	564	14	27	1	6	2,101	1	14	9		12	8		39,479	42,252
Sum	26,590	21,883	32,427	620	3,257	3,845	19,780	906,318	19,295	58,054	4,250	1,223	34,320	745	59	43,214	1,175,880

Table 78: Error analysis, entity class model 2 (sorted by decreasing accuracy)

Entity Class	Accu-racy	False Nega-tives	False Posi-tives	Size of cat. in ground truth	Tokens in cat.	Accu-rate pre-dictions	False Nega-tives	False Posi-tives
time na	93.4%	6.6%	8.6%	15.3%	42,252	39,479	2,773	3,735
attribute na	93.2%	6.8%	7.8%	11.7%	32,085	29,890	2,195	2,537
resource na	93.0%	7.0%	3.9%	12.9%	35,483	32,996	2,487	1,324
org-att specific	92.1%	7.9%	4.4%	1.6%	4,410	4,063	347	187
agent specific	91.3%	8.7%	10.2%	7.8%	21,515	19,646	1,869	2,237
location specific	90.7%	9.3%	11.7%	7.0%	19,247	17,456	1,791	2,324
org. generic	90.1%	9.9%	8.4%	7.1%	19,616	17,677	1,939	1,618
agent generic	90.0%	10.0%	5.1%	10.2%	28,013	25,221	2,792	1,369
organization	88.2%	11.8%	6.4%	22.4%	61,556	54,313	7,243	3,741
location generic	73.5%	26.5%	15.3%	1.6%	4,429	3,256	1,173	589
event specific	71.9%	28.1%	12.9%	0.3%	751	540	211	80
resource generic	71.7%	28.3%	18.1%	0.5%	1,397	1,002	395	221
knowledge	54.8%	45.2%	46.3%	1.2%	3,194	1,750	1,444	1,507
task na	29.6%	70.4%	50.8%	0.0%	98	29	69	30
resource specific	28.1%	71.9%	52.2%	0.5%	1,266	356	910	389

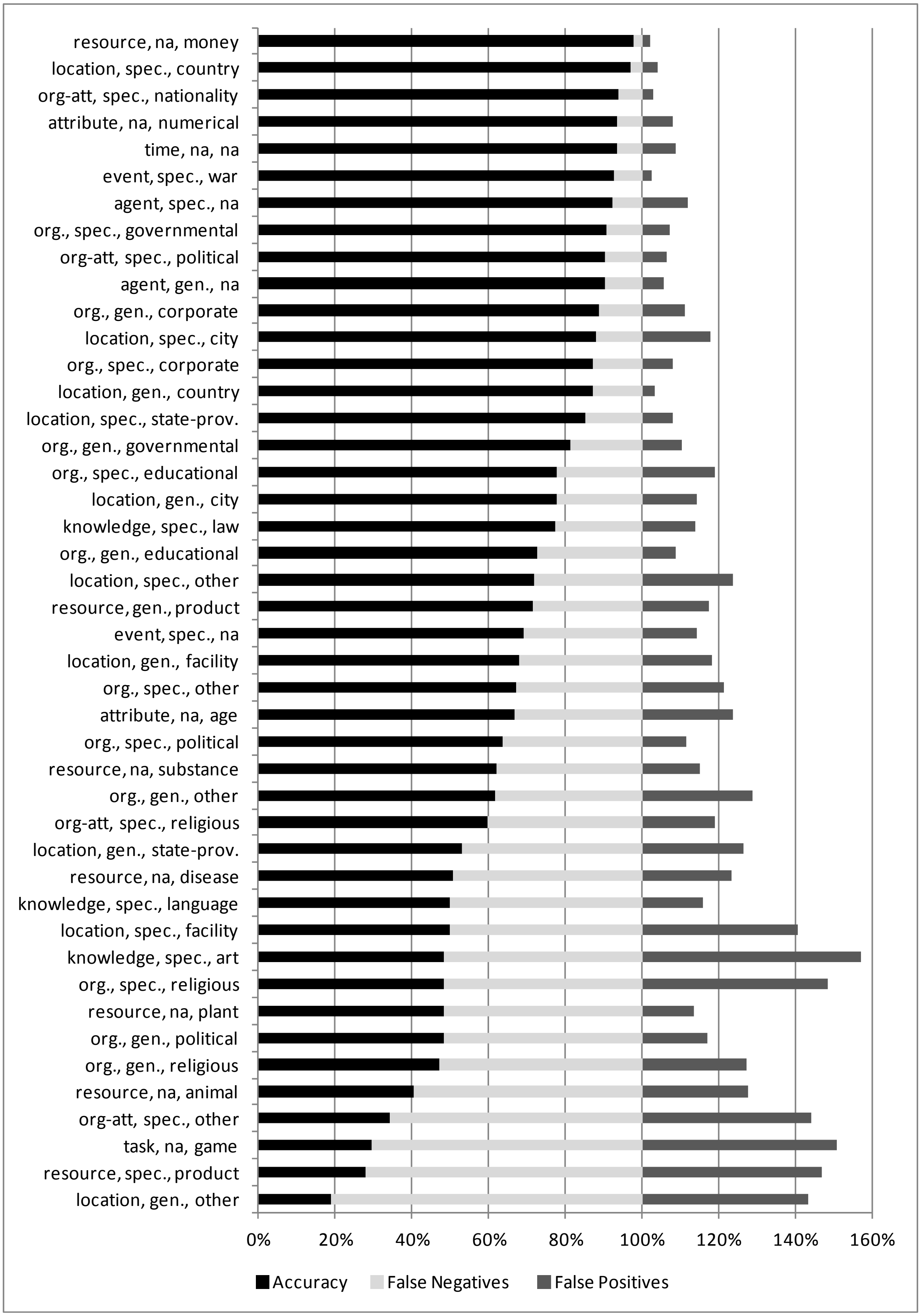
Table 79: Error analysis, entity class model 3 (sorted by decreasing accuracy)

Entity Class	Accu-racy	False Nega-tives	False Posi-tives	Size of cat. in ground truth	Tokens in cat.	Accu-rate pre-dictions	False Nega-tives	False Posi-tives
resource money	97.5%	2.5%	2.1%	11.5%	31,686	30,905	781	647
location country	94.4%	5.6%	4.9%	2.4%	6,701	6,329	372	326
attribute numerical	93.6%	6.4%	8.2%	11.3%	30,991	28,995	1,996	2,598
time na	93.3%	6.7%	8.7%	15.3%	42,252	39,439	2,813	3,760
org-att nationality	93.3%	6.7%	4.4%	1.3%	3,538	3,300	238	151
agent na	91.7%	8.3%	9.9%	18.0%	49,528	45,418	4,110	4,987
event war	90.2%	9.8%	2.7%	0.0%	122	110	12	3
organization gov.	88.7%	11.3%	8.5%	4.0%	10,925	9,691	1,234	906
org-att political	88.1%	11.9%	9.5%	0.2%	682	601	81	63
org. corporate	86.3%	13.7%	9.5%	23.0%	63,382	54,724	8,658	5,742
location city	84.5%	15.5%	17.9%	2.9%	7,889	6,667	1,222	1,450
location state-prov	80.4%	19.6%	9.7%	1.3%	3,530	2,838	692	304
organization edu	77.9%	22.1%	13.6%	0.5%	1,246	971	275	153
knowledge law	76.6%	23.4%	11.4%	0.3%	907	695	212	89
location other	70.8%	29.2%	26.2%	0.8%	2,083	1,475	608	523
attribute age	69.8%	30.2%	21.6%	0.4%	1,094	764	330	210
event na	67.7%	32.3%	16.5%	0.2%	629	426	203	84
organization other	65.9%	34.1%	21.0%	1.7%	4,669	3,077	1,592	819
organization political	63.2%	36.8%	9.7%	0.3%	798	504	294	54
location facility	62.8%	37.2%	21.8%	1.3%	3,473	2,182	1,291	610
resource substance	60.4%	39.6%	14.2%	1.0%	2,808	1,697	1,111	281
org-att religious	59.6%	40.4%	21.1%	0.0%	94	56	38	15
resource disease	51.3%	48.7%	17.4%	0.1%	378	194	184	41
organization religious	50.7%	49.3%	34.2%	0.1%	152	77	75	40
resource product	50.1%	49.9%	23.6%	1.0%	2,663	1,334	1,329	412
knowledge language	50.0%	50.0%	8.5%	0.0%	86	43	43	4
resource plant	48.5%	51.5%	12.7%	0.1%	198	96	102	14
knowledge art	47.3%	52.7%	58.6%	0.8%	2,201	1,040	1,161	1,473
resource animal	40.7%	59.3%	24.7%	0.2%	413	168	245	55
org-att other	34.4%	65.6%	35.3%	0.0%	96	33	63	18
task game	24.5%	75.5%	52.0%	0.0%	98	24	74	26

Table 80: Error analysis, entity class model 4 (sorted by decreasing accuracy)

Entity Class	Accuracy	False Negatives	False Positives	Size of cat. in ground truth	Tokens in cat.	Accurate predictions	False Negatives	False Positives
resource, na, money	97.7%	2.3%	2.1%	11.5%	31686	30958	728	662
loc., spec., country	97.0%	3.0%	4.1%	2.1%	5708	5538	170	234
org-att, spec., nat.	93.8%	6.2%	2.9%	1.3%	3538	3319	219	100
attrib., na, numerical	93.4%	6.6%	8.2%	11.3%	30991	28960	2031	2580
time, na, na	93.4%	6.6%	8.7%	15.3%	42252	39464	2788	3772
event, spec., war	92.6%	7.4%	2.6%	0.0%	122	113	9	3
agent, spec., na	92.3%	7.7%	11.8%	7.8%	21515	19849	1666	2649
org., spec., gov.	90.8%	9.2%	7.3%	3.1%	8404	7629	775	597
org-att, spec., pol.	90.5%	9.5%	6.5%	0.2%	682	617	65	43
agent, gen., na	90.2%	9.8%	5.8%	10.2%	28013	25263	2750	1562
org., gen., corporate	88.7%	11.3%	11.1%	5.6%	15305	13581	1724	1691
loc., spec., city	88.1%	11.9%	18.0%	2.7%	7512	6615	897	1452
org., spec., corporate	87.2%	12.8%	8.0%	17.5%	48077	41938	6139	3651
loc., gen., country	87.1%	12.9%	3.5%	0.4%	993	865	128	31
loc., spec., state-prov.	85.4%	14.6%	8.1%	1.1%	3133	2675	458	237
org., gen., gov.	81.4%	18.6%	10.4%	0.9%	2521	2051	470	237
org., spec., edu.	77.8%	22.2%	19.2%	0.4%	1001	779	222	185
loc., gen., city	77.7%	22.3%	14.3%	0.1%	377	293	84	49
knowledge, spec., law	77.5%	22.5%	13.8%	0.3%	907	703	204	113
org., gen., edu.	72.7%	27.3%	8.7%	0.1%	245	178	67	17
loc., spec., other	71.8%	28.2%	23.7%	0.7%	2014	1447	567	450
res., gen., product	71.7%	28.3%	17.5%	0.5%	1397	1001	396	213
event, spec., na	69.0%	31.0%	14.4%	0.2%	629	434	195	73
loc., gen., facility	67.9%	32.1%	18.3%	0.9%	2593	1760	833	395
org., spec., other	67.1%	32.9%	21.2%	1.2%	3326	2233	1093	600
attribute, na, age	66.9%	33.1%	23.8%	0.4%	1094	732	362	228
org., spec., political	63.8%	36.2%	11.4%	0.2%	647	413	234	53
res., na, substance	62.0%	38.0%	14.9%	1.0%	2808	1742	1066	306
org., gen., other	61.6%	38.4%	28.8%	0.5%	1343	827	516	334
org-att, spec., religious	59.6%	40.4%	18.8%	0.0%	94	56	38	13
loc., gen., state-prov.	52.9%	47.1%	26.6%	0.1%	397	210	187	76
resource, na, disease	50.8%	49.2%	23.5%	0.1%	378	192	186	59
know., spec., language	50.0%	50.0%	15.7%	0.0%	86	43	43	8
loc., spec., facility	49.8%	50.2%	40.7%	0.3%	880	438	442	301
knowledge, spec., art	48.5%	51.5%	57.1%	0.8%	2201	1068	1133	1422
org., spec., religious	48.5%	51.5%	48.4%	0.0%	101	49	52	46
resource, na, plant	48.5%	51.5%	13.5%	0.1%	198	96	102	15
org., gen., political	48.3%	51.7%	17.0%	0.1%	151	73	78	15
org., gen., religious	47.1%	52.9%	27.3%	0.0%	51	24	27	9
resource, na, animal	40.4%	59.6%	27.7%	0.2%	413	167	246	64
org-att, spec., other	34.4%	65.6%	44.1%	0.0%	96	33	63	26
task, na, game	29.6%	70.4%	50.8%	0.0%	98	29	69	30
res., spec., product	28.0%	72.0%	47.0%	0.5%	1266	354	912	314
loc., generic, other	18.8%	81.2%	43.5%	0.0%	69	13	56	10

Figure 11: Error analysis, class model 4



3.4.8 Integration of prediction models into end-user software

Once the accuracy of the final models had been evaluated, the remaining task for this project is to make the models publically available in a software product. The goal with this step is to provide this prediction technology such that people from different backgrounds with potentially very little expertise in natural language processing can use it for their text analysis projects. The integration process is described in detail in chpater 4.1 in the operational chapter.

3.5 Limitations

The prediction capabilities of the built model strongly depend on the training data. Even though I chose a training dataset with a large number of examples and a suitable set of categories and category attributes, there are several limitations with the BBN dataset: First, the data are from a single source, namely the Wall Street Journal. Second, the data represent a single genre and well defined domain, i.e. newspaper articles. Thus, the models can be expected to generalize with less accuracy to different genres and writing styles than to the training domain. Third, the articles are from 1989, which implies that terms and phrases might be outdated, and many agents and other entities that are relevant today might not occur in the data. This issue might already have been mitigated to some degree by using a lookup dictionary that is based on current news data. Fourth, since the learning data is in English only, the resulting models cannot be expected to generalize to other languages. Fifth, BBN contains only a few types of activities, which limits our ability to predict task and events of the type that the meta-network model expects. Sixth, the data contained various inconsistency issues as outlined in section 3.3.1 that we corrected for as we found them prior to learning. However, when evaluating the results, we saw that a handful of entities in the marked up files crossed line breaks or paragraph breaks in a way that a multi-word expressions are interspersed with a few additional spaces, e.g. “Cie.   Fianciere de Paribas”. The learner has picked up on these few problematic cases and developed some reasoning about them. While these cases are noisy and could impact the accuracy of the overall model, they might reflect scenarios that can be found in new data as well. Overall, the outlined limitations can be addressed by enhancing the learned models or building new models by learning with more recent data that originates from more sources, covers more domains, and contains more examples of activities.

Including other feature types, using a different combination of feature types, or applying a different iteration rate might all have led to better and potentially more accurate or more robust prediction models. The parts of speech tagger that was used as a feature type for this project is not error free to begin with, but achieves about 93% accuracy. This issue represents a general limitation with features that require pre-processing of the text data: the pre-processing routines

are imperfect in terms of their accuracy. As a result, errors with these routines get propagated throughout the learning process. Furthermore, generating these features further increases the runtime costs (S Sarawagi, 2008).

Finally, training models with CRF has high run time costs. For example, building the final class label prediction models that outputs a meta-network category along with a specificity attribute and a category subtype per entity took nine days. This time constraint requires careful planning of experiments for testing the impact of features on prediction accuracy. Such experimentation is further complicated by the fact that small iterations rates (in the case of this study less than 300) do not necessarily allow for extrapolating to results with higher, more appropriate iterations rates. However, once the models have been built, applying them for inference to new data is speedy, as demonstrated in the next chapter.

3.6 Conclusions and Future Work

Two main contributions have been made with this project: First, I have developed a highly accurate computational solution to the extraction of entities from text data. The approach I used for building these prediction models is interdisciplinary in that it combines a theoretically grounded model from organization science for informing the definition of relevant entity classes with cutting edge methods from natural language processing and machine learning. The obtained accuracy rates are on a par with rates from alternative, top-performing entity extractors. However, beating benchmarks was not the goal here. Rather, the objective was to build an entity extractor that end-users can apply in the process of constructing one-mode and multi-mode network data that support them in answering substantial question about socio-technical networks. Delivering such a product as part of a publically available tool (AutoMap) is the second contribution with this project. Going from learned models to usable technology involved its own challenges. An example is the designing of rules for handling false positives such that end-users are best supported in their needs, which required different rules than the ones I applied for the rigorous assessment of the accuracy of the learned models.

At the beginning of this chapter I had defined several sub-goals for this project. Table 81 summarizes how they have been met, and points out the practical relevance of these objectives.

Table 81: How project goals have been met and practical relevance of solutions

Goal	Delivered outcome	Practical relevance
1. Automation	- Scalable and publically available solution to entity extraction.	- Supports analysis of large text data sets. - Reduces time and labor costs for

		thesaurus construction.
2. Abstraction of terms to concepts or higher level aggregates	- Text level terms are associated with meta-network categories that encode different levels of detail, namely a specificity value and/ or a subtype per entity. Since prediction results might differ between reducing a complex model to a simpler model and training a simpler model separately, models at five different levels of granularity were built and evaluated.	- Allows user to choose the level of granularity the best fits their needs. - Allows user to balance accuracy and granularity based on their needs.
3. Generalization	- Ability to identify new and unseen instances of entity classes and entity attributes.	- Faster analysis of and adaption to new corpora. - Reduced time and labor costs for thesaurus construction.
4. Support users in addressing substantial and meaningful questions about socio-technical networks	- Ability to extract meta-network data from texts. These data can be further analyzed in ORA, which provides metrics defined over non-generic entity classes.	- Move beyond the extraction and analysis of social networks (agent by agent connection) or generic one-mode networks to the analysis of multi-mode, socio-technical networks.
5. N-gram detection	- Correctly identify boundary and class of multi-word entities.	- The boundary class models that facilities the detection of entities (unigrams and multi-word expressions) is particular useful for constructing one-mode networks and content analysis. Once these entities are identified, they can also be classified, which supports the construction of multi-mode networks.
6. Allow terms to belong to multiple entity classes instead of just one.	- Ability to assign identically spelled terms to multiple meta-network categories. - Differentiate terms based on predicted label and for the NORP class also on part of speech.	- Contributes to the disambiguation of homonyms. . - Reduced loss of relevant information over current thesaurus creation technique in AutoMap.
7. Entity Extraction (as opposed to focus on Named Entity Extraction)	- Ability to extract entities that are a) referred to by a name or not and b) instances of classes where many entities are not named.	- Allows for distinguishing between generic and specific entities, which is particularly useful when term presenting roles of social agents subsume a large number of references.

From a NLP perspective, the findings from this study imply several conclusions about the impact of engineering decisions and particular features types on the accuracy and required training as summarized in Table 82. The most unexpected finding was that large differences in model complexity (number of prediction classes, which impacts the number of states and edges in the

probabilistic graphical model) lead to only small differences in accuracy rates. In contrast to my hypothesis, less complex models are not necessarily more accurate than more complex ones. With respect to the per class accuracy within prediction models, the results indicate that high accuracy is not a matter of class size, but low accuracy was only observed for small classes. Considering both findings together leads to the following recommendation for designing entity extractors: it is critical to find a good balance between consolidating small class into larger aggregates and avoiding the fusion of classes with very different (weights per) features, which potentially dilutes the expressiveness of features.

Table 82: Impact of variable on outcomes

Variable	Accuracy	Training Time
Baseline	large	small
Syntax Features (POS)	small	small
Lexical Features (Dictionary, hard match)	large	small
Iteration Rate	large	large
Complexity of Category Schema/ Model	small	large

With respect to feature types, in my results the parts of speech tags were the weakest contributor to accuracy. This could be due to the fact that parts of speech tags are not orthogonal to other clues, or that other syntax features might be more appropriate. In future work, it seems worthwhile to test more advanced syntactic features, such as the constituent of a parsing tree that per token. Also, the results show that it is important to test the isolated impact of each baseline feature as gains from eliminating non-contributing features can be substantial.

When the goal is to provide the entity extractor to end-users, it is furthermore crucial to test if the models that the learning system outputs are readily usable for inference in another environment. In the case of this study, adjustments were needed that had to be represented in the learning output directly and thus required retraining of the models after these discrepancies were detected. To harness those situations, I recommend plugging in a first output model, e.g. one from learning with the feature baseline only, into the external inference environment in order to identify any necessary adjustments. This eliminates time for retraining when it comes to building the final models with the best and most robust feature set found.

The presented solution involves several considerations that are particular to the goal of aiming for practical usefulness of the models, and are fairly independent from the NLP and machine learning methods part: the models were built such that they are particularly suitable for extracting relevant entities from documents about socio-technical systems. One strategy for achieving this goal was to use a theoretically grounded model from organizations science to inform the selection of relevant entity classes. Furthermore, the generated models support the

consideration of entity classes where many instances are common nouns and noun phrases, e.g. in the resource class. Specific and generic entities, which often means entities that are referred to be a name or not, are distinguished from each other. This is important for keeping roles versus specific references to agents separate from each other. Finally, I have designed and implemented the way that outputs are generated from these models such that the output data include entities for which a non-outside boundary label has been found but no class label and vice versa, or for which other discrepancies between both labels exist. For assessing the accuracy of prediction models, these cases were handled differently, i.e. more rigorously as defined by standard information extraction assessment procedures. There, such conflicting cases are considered as inaccurate and are disregarded from final outputs. However, for practical applications of parsing entities from news wire data and other accounts of event coverage, optimizing on error reduction might be less important than retrieving the largest possible set of potentially relevant entities. The presented solution implies the assumption that end-users might be willing to comprise some accuracy in label assignment (precision) for a greater coverage of retrieved entities (recall) for two reasons: First, entirely rejected entities might be hard to retrieve otherwise. Second, finding a class for yet unlabeled but retrieved entities or correcting the class of entities for which discrepancies are explicitly marked as such might be more acceptable than knowing that those cases are returned altogether.

The lowest performing classes in the models I built are activities in general (tasks and events), as well as knowledge and specific resources. In future work, these limitations can be addressed by using additional learning data that contains more examples for these classes, and by only merging classes that are similar in content as well as (weights of) features. For this project, category merging was driven by resembling the categories in the meta-matrix model and avoiding overly small classes. Furthermore, the learning data for this project was from a single, somewhat dated source and genre. In order to provide more flexible models with a potentially higher capacity to provide correct predictions for corpora that feature more current style and content, we should also consider more recent training data from multiple domains and genres.

4 From Experimental Results to Practical Applications

This chapter describes the transition from the knowledge gained with the experimental work from the previous two chapters to practical implications of the found results. I explain the steps that are necessary for making the theoretical knowledge operational, and outline the limitations that result from brining this knowledge into application contexts.

4.1 Impact of Coding Choices about Reference Resolution and Windowing on Network Data and Analysis Results: Implications and Recommendations for Applied Work

The results for the impact of reference resolution on network data greatly differ depending on the chosen approach for normalizing nodes: if node IDs that reflect the true identify of a node are available, I recommend working with these IDs instead of using node names as proxies for node IDs. The ORA software supports this approach by allowing for node ID's that are different than the node names. For example, homonyms can be disambiguated by different node IDs. If no such node IDs are available, which is typically the case for networks extracted from texts, and nodes are disambiguated and consolidated based on their spelling, conducting any reference resolution technique is not necessarily worthwhile with respect to key player analyses and the majority of graph-level network analytical measures. However, the obtained results will not resemble the ground truth. To prevent his outcome under the condition that no alternative node IDs are available, I recommend not to conflate nodes based on their spelling, but trying to perform node disambiguation and consolidation as well as possible. The following strategies can be used to this effect:

- After important raw text data into a text analysis tool and prior to performing reference resolution, the following techniques can be used; all of which are available in AutoMap:
    - Disambiguate entities based on their part of speech (Diesner & Carley, 2008b).
    - Identify meaningful multi-word expressions such that some individual tokens are aggregated into distinct units.
    - Identify the node class of entities, and disambiguate nodes and multi-word expressions based on the node class.

The entity extraction models that were developed in the previous chapter help with all three of these pre-processing steps. Therefore, the entity extractor built herein not only serves the identification of nodes for the construction of network data, but also facilitate pre-processing steps that are crucial for relation extraction.

If the resources for performing reference resolution are limited, I further recommend focusing on co-reference resolution rather than anaphora resolution. This decision further requires sticking with key player analysis instead of the calculation of network metrics when analyzing the network data.

When it comes to selecting a reference resolution tool or technique, differences in accuracy do matter, especially if the harmonic mean or recall and precision is below 90%. Therefore, I recommend looking for the tool that achieves best accuracy data on a given domain or genre.

When connecting nodes into edges, caution is needed if windowing is chosen as the link formation mechanism. This is because the rate of false positives can be very high such that nine out of ten links can be false positives at a decent window size. To lower this risk, the following strategies can be applied, e.g. in AutoMap:

- Code roles and attributes of nodes not as a node class, but only as features on nodes of other classes. A solution to this point is also developed in the next chapter.
- Disregard overly common nodes for entity extraction. These nodes can be identified, for example, by (weighted) term frequency metrics on entities (Diesner & Carley, 2004; Yang & Pedersen, 1997).

Based on the empirical results on the impact of proximity-based link formation on network data and analysis results, the following recommendations can be made:

- If a corpus contains an indistinguishable mixture of syntactic and semantic link, at least 90% of all links are covered with a window size of seven. Syntactic links are natural by-production of language production rules, such as links between adjectives and the proper nouns they modify. Semantic relationships are more independent from language production rules, and can be orthogonal to these rules, such as the description of the type of social relationship between two agents in text data.
- If syntactically motivated links are disregarded, more than 90% of true links are typically found when using a window size of twelve. This result is robust cross genres, types of semantic relationship, and node classes.
- Finally, when using windowing as a link formation method, one needs to keep in mind that the amount of false positive links can be enormous. Again, this risk can be mitigated by coding attributes of nodes, such as roles and titles, as properties of the respective nodes instead of separate node classes.

4.2 From Learned Models to Usable Technology: Integration of Prediction Models into End-User Software

Once the accuracy of the final prediction models for entity extracted had been evaluated (outcome of chapter 3), the remaining task for that project was to make the models publically available in a software product. The goal with this step is to provide this prediction technology such that people from different backgrounds with potentially very little expertise in natural language processing can use it for their text analysis projects. In the following, I describe the types of challenges (marked in italics at the beginning of paragraphs) that can occur throughout this process using the example of AutoMap. However, many of these challenges generalize to providing such a technology either as a stand-alone, end-user tool, or integrating it into existing systems, which implies a variety of constraints.

1. Training of models: For end-user applications, each model needed to be trained with all training folds and no hold out fold. I used the same feature configuration as I did for the last the final round of accuracy assessment (Table 71). The upper bound on training time is constrained by the most complex model, which takes about 10 days to complete.

2. Separate inference engine: Next, I built an inference engine that uses outputs from the learning process (details below) in order to make predictions on new and unseen text data, and added this inference engine to AutoMap. This engine reuses part of the learning code, but also requires new code. The outputs from learning that needed to be migrated into AutoMap are a model file (number of features and weight per feature), a features file (each feature and its ID), and a coding files that associates numeric values of prediction classes with logical values of those classes (details on that in the next paragraph).

3. Different inference systems: AutoMap features a GUI version and a script version. While they share some code, integration had to be done for each version individually. Therefore, every step described in this section was performed and validated for the GUI version and the script version separately while making sure that they produce identical results.

4. Incomplete learning output representation: When I integrated the first set of models into AutoMap, both, the retrieved entities and their classifications, seemed highly inaccurate. Investigating this issue revealed a critical difference between the models as they are held in memory after training and prior to evaluation, and the models that get stored out to disk. This difference is specific to the CRF technology I adopted for this project, but might generalize to other CRF implementations: when the models are temporarily stored in memory, they also keep the information about which numerical value for each class label (boundary and category) maps to which logical value for each of these labels. The CRF implementation picks these numerical

values internally, implicitly and in random order. This procedure applies not only the boundary and category labels, but also to the features. Since I added new features to the CRF baseline, there were also numerical values for each part of speech tag and each entry in the lookup dictionary. The problem here is that once the models are stored out, this mapping is not output by default or represented in any output file. Thus, I had to re-engineer this mapping if I wanted to make my models work. However, I could not find any apparent logic, regularities, or systematic way according to which this mapping or assignment of numerical values to labels happens. Therefore, I had to retrain all models with the exact same features such that the outputs now include this mapping. This retraining had no impact on model accuracy; the only difference was that the output files contained the needed mapping information.

5. Routine incompatibility: The resulting models led to greatly improved prediction results in AutoMap. Nevertheless, the results still seemed less accurate than what the final results from the k-5 cross validation led me to reasonably expect. This could be due to poor generalization capabilities of the models, or technical issues with integrating the models into AutoMap. Exploring this issue further first revealed a problem that might generally apply to situation in which new routines are plugged into existing, larger systems, and where the new routine reuses available functionalities. In my case, this existing routine was the part of speech tagger. The change regarding the tags for tokens involving digits did conflict with the POS implementation and tag set already available in AutoMap. I solved this issue by adding the parts of speech tagger that I had added to the CRF environment into AutoMap. The difference between both taggers is small, but makes a big difference for the accuracy of prediction models.

6. Input representation issues: At this point, the prediction quality of the models still seemed lower than what I expected; still hoping that this drop in performance was not due to the quality of the models themselves, but the way they were integrated into AutoMap. The next issues that I identified were differences between how input data are represented in AutoMap versus how the learning data were formatted. In order to solve this problem, I went back to the BBN data and identified these formatting particularities by carefully going through the data and paying special attention to non-letter, non-digit characters. Next, I adjusted the formatting of the texts that the prediction models in AutoMap take as an input such that they resemble the following idiosyncrasies: in BBN, sentence marks are space-separated from the last word in a sentence, while other dots, such as in Mr. or U.S., are not space-separated from the tokens they belong to. I reused the sentence splitter that I had previously integrated into AutoMap for the purpose of determining sentence boundaries and distinguishing them from other dots (Diesner & Carley, 2004). Also, in BBN, commas have a space character right and left from them, and the same is true for various other non-digit, non-letter symbols, e.g. hyphens and percentage signs. However,

there are exceptions to this rule, e.g. dashes within multi-word units, such as in “money-market”. Finally, genitive markers of nouns, e.g. “parent ’s”, and negations of verbs that are part of the word, such as “did n’t” or “is n’t”, are space-separated from the main verb as shown in the examples above. Once those changes were made, the prediction accuracy of the models in AutoMap was improved and seemed satisfying.

There are two ways to realize these changes: they could be represented only internally, or they adjusted formatting could be shown to the user as well. Since one of the main purposes with these models is to generate thesauri that users can apply to the text data when generating networks data, it is crucial that the entities in the prediction outputs match the text data. Thus, I decided to store the modified text data so that users can load them for further work if needed.

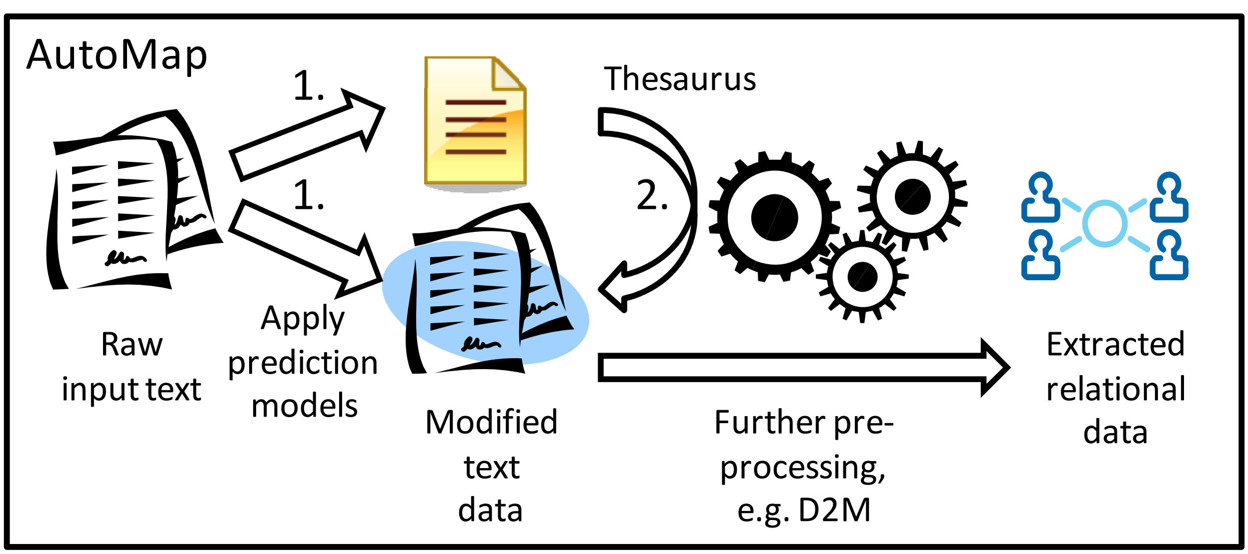
7. Trading off conciseness and certainty for recall: Next, additional changes were necessary to ensure that the new prediction routines support end-users in addressing substantial and meaningful questions about socio-technical networks. First, I adjusted the rule set for combining the boundary and category model (according to the boundary dominating policy) such that fewer entities are missed than with the rigorous rule set used for model assessment up to here. During error analysis I observed that oftentimes, the boundary label is correctly indicating an entity and a class label is suggested as well, but the category prediction is not perfectly accurate and rather returns a reasonable alternative. For example, “consultants” were predicted as a generic organization, but the ground truth labels them as a generic agent. For the end user, such false positives might still be relevant: for practical applications of entity extraction, recall is often considered as more important than precision (S Sarawagi, 2008). This is because incorrect class labels can be corrected for by hand, but entities that are not returned as a potentially relevant hit at all would be hard to retrieve otherwise. Therefore, the modified combination rules for the end-user tool penalize the following discrepancies less for severely than during accuracy assessment: tokens with a non-outside boundary label but no class label as well as the inverse case are both output and are explicitly marked as potentially useful additional hits. These tokens might be false positives or true negatives. Except for these changes, the same combination rules as described above are applied.

8. Category adjustment: Finally, BBN contains four categories of the NORP type (nationality, other, religion, political, for details see Table 59). Instances of NORP are either specific agents or organizations or attributes. Since end-users might want to be able to distinguish between these cases, I separate them for application in AutoMap based on their parts of speech after checking the hits that this category returns: All instances that are labeled as nouns (NN, NNP, NNS, NNPS) or personal pronouns are categorized as specific organizations of the respective subtype (if applicable in the entity class model), all other instances are assigned to the attribute category.

9. Output representation issues: A naturally suitable output format for the entity lists or thesauri generated by the prediction models would a tab delimited format. However, in AutoMap, these types of output have to be in csv format. The problem here is that retrieved entities may contain commas, which would mess up csv outputs. Note that these outputs are used for further computations and thus have to adhere to certain regularities. In order to accommodate this change from tab delimited (initial output) to csv, I remove the commas from texts after prediction; adding this change to the text files that get stored out when the prediction outputs are generated.

The models can be used in AutoMap as follows (Figure 12 shows a schematic depiction of the intended workflow in AutoMap): The boundary prediction model extracts uncategorized entities, which can be unigrams or multi-word expressions. These entities can be used for conducting content analysis, or as nodes for constructing one-mode networks. In the output from the boundary prediction model, the extracted entities are actually assigned to the "knowledge class", because in the meta-matrix model, this class represents nodes in generic, one-mode networks. Thus, "knowledge" is also the default class in AutoMap. All four entity class models were also integrated into AutoMap. The output from all prediction models can serve as baseline thesauri. This eliminates or reduces the need to construct thesauri by employing alternative NLP routines as described in section 5.2.2.1, which is considerably more time consuming and requires further human decisions. Furthermore, the outputs from the prediction models can be used to consolidate synonymous entities that have different surface forms. This a form of co-reference resolution and helps to alleviate the issues with disambiguating and consolidating nodes based on spelling as identified in the previous chapter.

Figure 12: Workflow of using prediction models in AutoMap



The output from each of the five models contains the following information:

- The extracted entity.
- A conversion of multi-word expressions into a single token via concatenation, e.g. United Nations into United_Nations. This helps to keep entities together when they appear as nodes in a network, and complies with the standard node formatting style in AutoMap.
- The meta-network category per entity.
- Depending on the chosen prediction model, zero, one or two attributes per entity that represent the specificity and/ or subtype value if applicable. Specificity, for example, can have the values "specific", "generic", or "not applicable". In the latter case, no attribute gets output.
- The part of speech of each token in an entity, i.e. multiple parts of speech in the case of multi-word expressions.
- The cumulative frequency per entity as inferred from the text data.

The frequency per entity is only increased if two entities agree in spelling including capitalization, as well as in meta-network category, any attribute per category, and parts of speech. This helps to disambiguate entities based on their part of speech, which is a new functionality in AutoMap. It also helps to consolidate entities that differ in capitalization only during thesaurus application. This could for instance apply to entities that typically occur in lower case, e.g. "apple" (the common noun), but are capitalized at the beginning of a sentence, and are still different from words that are orthographically the same, but have a different meaning (such as "Apple" as the company). I defined these rules for disambiguation and consolidation in order to prevent the loss of information that we had previously disregarded in AutoMap.

10. Usability: Since the proper application of these various models in AutoMap (or anywhere else) is not necessarily intuitive to end-users, different types of documentation are needed. In order to assist users in selecting the model that best fits their needs, I added a decision tree that differentiates the models based on the level of detail they encode and their accuracies. Also, I wrote a user's guide for this sub-routine that is part of the AutoMap help system.

11. Reusability: Finally, I built the learning technology for this project such that it can be re-used by CASOS members to train models that are based on modified or different ontologies, or use different features.

In summary, integrating the learned models into an existing software product implies additional tasks and challenges that are not necessarily foreseeable during the model construction state, and might even require the re-training of the models. Overall, the time costs for making the learned

models publically available in a ready-to-use fashion are significant: the described integration process took about as long as selecting features and training and testing the models did together.

5 Comparison of Relation Extraction from Texts including Entity Extraction to Alternative Methods for Network Data Construction in Application Contexts

In this chapter, I demonstrate the end-to-end process of going from raw text corpora to network data to analysis results. This chapter puts the knowledge gained in chapter 2 about of the impact of coding choices on network analysis and the technology developed in chapter 3 for entity extraction into different application contexts.

5.1 Motivation and Research Questions

During the formal evaluation of the prediction models (chapter 3), state of the art accuracy rates had been achieved. However, the ultimate purpose with these models is to employ them for practical text coding projects, where the text data might be from different domains or of different writing styles than the data used for training the models. Therefore, the first research questions answered in this chapter is:

1. *How do the prediction models perform in real-world application scenarios?*

Here, performance is operationalized as the suitability or fitness of the generated thesauri for extracting socio-technical networks from different corpora so that the resulting data can be used as input to classic network analysis routines, such as identifying key entities. In general, in application contexts, the text data might differ in many dimensions from the data that a model was trained on. In this study, I am testing three of the most common dimensions, namely the time at which some text data were written, the genre, and the writing style. Table 83 compares the corpora used in this study, which are introduced in more detail throughout this chapter, to the data used for model training on the selected dimension. This comparison shows that among the considered corpora, the Sudan data are most similar to the training data, while the Enron email data are most different from the training data. Therefore, I hypothesize that the prediction models perform best on the Sudan data, second best on the Funding data, and least well on the Enron data.

Table 83: Comparison of corpora used in application scenarios to used for model training

Dimension	Training Data	Sudan	Funding	Enron
Time	1989	2003-2010*	1984-2006*	2001*
Genre	Newswire	Newswire	Scientific writing*	Emails*
Writing Style	Formal	Formal	Formal	Informal*

* = different from training data

The second research questions addressed in this chapter is motivated by the fact that relation extraction is one among many methods for constructing network data based on text data (for a review of these methods see chapter 3.2.3). However, there is a lack of research on how these different methods compare with respect to their outcome, i.e. the properties of the generated network data. Therefore, the second research question is:

2. *How do the network data and network analysis results obtained by conducting relation extraction which uses the entity extractor developed in chapter 3 compare to alternative methods for constructing network data from the same corpora?*

The comparison of network data and analysis result in this chapter is operationalized as follows: based on the experimental results from chapter 2, I had developed recommendations for practical applications of these methods in section 4.1. Based on these recommendations, it seems appropriate to compare the networks with respect to their size and the key entities that are identified according to selected network metrics. The latter strategy had also been identified as suitable and was therefore used for comparing networks generated with different coding choices in section 2.7.1. In addition to these strategies for network comparison, the similarity of any pair of network data constructed with different methods is assessed by creating the intersection of these networks in terms of nodes and edges. Since these network data were generated with different methods, which involve different pre-processing steps and pre-processing material, e.g. different thesauri, I hypothesize that these network data do not to resemble each other. Instead of designing or hoping for convergence of these methods with respect to network structure, the contribution here rather is to identify the differences and commonalties between the resulting data. This knowledge can help us to understand what different views on a network are provided with the tested methods.

In summary, the focus of this chapter is on the impact of methodological choices on network data. This approach is similar to the work presented in chapter 2, where the impact of choices about pre-processing and link formation - all of which also apply to the methods presented in this chapter - was tested. The difference is that while in chapter 2, I used ground truth data to be able to precisely identify these impacts, in this chapter; I use various real world data sets for which no ground truth data is necessarily available. This is possible because in chapter 3, I had used ground truth data to build the prediction models whose performance is contrasted against alternative methods for node identification in this chapter. Moreover, bringing the prediction models into application contexts for which no ground truth data is available is highly relevant as is resembles common, real-world analysis scenarios. With chapter 4, I had started to facilitate the transition from experimental results and models to practical applications. The current chapter also serves this purpose, and continues at where chapter 4 had stopped by illustrating selected

methodological steps involved in the end-to-end process of coding texts as networks. In order to illustrate the potential utility of this procedure, I provide exemplary, substantive research question that can be addressed by going through this process and further analyzing the resulting network data. The comprehensive analyses needed to answer these research questions would require separate studies, which are beyond the scope of the thesis. The point here is rather is show how the methods and tools studied up to here in this thesis can be practically employed in an information and efficient fashion.

5.2 Application Context I: Sudan Corpus

Previous network analysis of the Sudan are confined to a few qualitative studies (Elageed, 2009; Lobban, 1975). Conducting participating observations, interviews, or surveys to collect network data on the Sudan and South Sudan is expensive or even infeasible for the following reasons, which might also apply to other geo-political units: the Sudanese population is large (over 45 million people, estimated), the Sudanese people speak over 130 languages, mainly Arabic and/or English (Lewis, 2009), and the literacy rate there is low (61%) (Central_Intelligence_Agency, 2009). As an alternative source of information about this country, one can draw from the large amounts of open source text data that are provided about the Sudan. Section 5.2.1 describes the dataset in detail.

The presented study of is part of a larger multi-university research initiative (MURI) in cooperation with East Carolina University (ECU) and Rhode Island College (RIC). The goals with this MURI are to (K.M. Carley):

- Develop theories and computational techniques for modeling the adaptive behavior of groups in asymmetric threat environments.
- Identify and investigate various dimensions of socio-technical networks in the Sudan with a focus on culture.
- Delivering software products that facilitate the fast collection and assessment of these networks.

For the purpose of analyzing socio-technical networks of geopolitical systems, including networks of sub-state and non-state actors, network analysis has been previously employed as a stand-alone method (Erickson, 1981; Hämmerli, et al., 2006) as well as a method complementing other techniques, such as regression analysis (Humphreys, 2005). However, direct or remote access to such real-world networks can be hard to impossible for analysts in the cases of covert and past networks, such as illicit groups and bankrupt enterprises (Baker & Faulkner, 1993; Malm, Kinney, & Pollard, 2008). Nevertheless, the networks perspective has been employed to analyze covert organizations and ways or organizing, such as co-offending, trafficking, and

white-collar crime (Baker & Faulkner, 1993; K.M. Carley, Lee, & Krackhardt, 2001; Howlett, 1980; Reiss, 1988; Sarnecki, 2001; Seibel & Raab, 2003). In these cases, archival data including confidential as well as open source material can help to collect network data (R. Burt & Lin, 1977). In prior work, people have used text data to answer the following kinds research questions from a networks perspective:

- Who are the key individuals and groups in a region? (Hämmerli, et al., 2006; P. Schrodt, Gerner, & Yilmaz, 2004; P. Schrodt, Simpson, & Gerner, 2001)
- How does their importance develop over time? (K. M. Carley, et al., 2007)
- What dynamics drive the formation of strategic alliances between actors with potentially conflicting interests? (Fitzmaurice, 2000)
- What resources are involved when social agents are in conflict with each other? (Humphreys, 2005)

5.2.1 Data

I put together the Sudan Corpus by using a two step process that is described in detail in this section. This process involved downloading documents from the LexisNexis Academic database, and deduplicating and cleaning the downloaded files by using software I wrote for this purpose. The same or similar strategies might be useful for other for collecting corpora about countries and geographic regions from open source document collections. These strategies are based on my explorative hands-on work with the data and testing of different choices, such as various search terms and cut-off values. Several heuristics were developed and used as documented herein, and these rules might need adjustments when used for building other corpora.

For searching LexisNexis, I used the "power search" as the type of search, "Sudan" as the search term, "major world publications" as the data source, and constrained the search for the "country" category on "Sudan". A total of 119,859 documents matched these search criteria. As of March 2011, LexisNexis Academic allowed for retrieving 3,000 documents at a time, and downloading 500 at a time; resulting in 246 batches of documents to be manually downloaded. I downloaded the text bodies along with the meta-data that LexisNexis Academic provides. Meta-data are marked by explicit index terms, such as "country", e.g. Sudan, and "city", e.g. Khartoum. The meta-data categories and values per category are defined and assigned by LexisNexis Academic without further documentation on this process.

I built a parser to split the batches into individual files, and outputs one text file per article. For each article, the parser identifies the source, publication date, title and actual text body if provided. Since these items are not marked by index terms, I defined data-driven rules for identifying them with high reliability. For cases in which the publication date could not be parsed

out, I use the load date, which is a meta-data field, as a proxy. Manually comparing load dates against the publication dates suggested that the load dates are the same or a few days after the publication date.

I set up a database to manage the Sudan corpus; which allows for filtering on meta-data. It is common that an article released by one news agency is published by multiple newspapers; leading to redundancy in reporting of events. I addressed this issue by using the following deduplication strategy: articles with the exact same publication date and title are considered as redundant and were removed. This first round of deduplication reduced the dataset by 4.3% or 5,109 files. The corpus was further reduced down to articles relevant with respect to Sudan by keeping only the files that meet both of the following two criteria: (1) The title contains the terms “Sudan*”, “Darfur*”, or “Khartoum*”. The stars are wildcards. (2) The values for index terms “geography” and/or “country” exceed 90%. These two routines together removed another 32,184 or 28.1% articles from the corpus. Further inspection of the data showed that many articles are reports of scores from sports games. I removed articles where the “subject” category contained “soccer”, “basketball”, “tournaments” and “athletes”, which were 1,513 files or 1.8% of the remaining data. Since some articles about sports can be relevant for studying social systems, I kept articles where the “subject” contained “sports”, “Olympics”, “stadiums”, and “arenas” unless these articles had been removed by the previous steps. At this point, the corpus still had articles that very highly similar to each other. In order to remove near-duplicates, I disregarded corrections of previously published articles (437 files). Next, I sorted the articles by publication date, title, and source in increasing order. I eliminated those that matched in the first four words of title and were published within a maximum time distance of three days (minus another 1,217 files).

The remaining bodies of the articles still contained index terms and additional information that are not part of the main content and headline, and would be considered noise when performing text analysis. To correct for this issue, I created an instance of the corpus from which I removed the bylines, highlight lines, and copyright notice from each article. Also, I disregarded anything that was not a header or the text body, e.g. the phrases “passage omitted” and “Text of report in”. The last step was based on a set of self-defined key words and phrases that indicate the beginning and end of headers and bodies, or serve as indicators for irrelevant lines and phrases that are intermitted within the body.

Next, I added a sentence mark at end of each headline. For the vast majority of articles, this helps to let the headline look like a real sentence to any subsequently used routine or tool. However, if the headline already has a sentence marker, e.g. a question mark, this will result in two delimiters for an end of sentence.

Finally, I checked if the cleaning techniques had reduced any articles to something not useful for text analysis anymore, such as nothing but section markers or image captions. Going from the smallest to the largest texts, this step eliminated 12 more articles. In total, the cleaning techniques reduced the corpus by 33.8% or 40,471 articles to 79,388 files. Table 84 shows the number of articles per calendar year in the final Sudan corpus.

Table 84: Articles per year in Sudan corpus

Calendar year	2003	2004	2005	2006	2007	2008	2009	2010
Number of articles in corpus	4,507	10,059	7,837	11,076	12,243	10,713	10,410	12,543

5.2.2 Network Data Construction Methods

The same network data construction methods are used for the three different application scenarios in this chapter is possible. For the Sudan corpus, the following four methods were used:

1. Perform text coding with the data to model process (D2M) in AutoMap (explained in section 5.2.2.1). This process involves the construction of a thesaurus.
2. Same as above, with the difference of using a thesaurus generated by the entity extractor built in chapter 3 (5.2.2.2).
3. Construct network data from meta-data contained in the Sudan corpus (section 5.2.2.3).
4. Work with subject matter experts to constructed network data that can be considered as ground truth data (section 5.2.2.4).

5.2.2.1 Network Data Extraction from Texts Using the Data to Model Process

The data to model (D2M) process was defined by Carley et al. (2011), and is designed for going from texts to multi-mode, socio-technical networks to analysis results. The process is still evolving, and has been used for multiple text coding projects at CASOS. Also, the process has been tied to the CASOS tools, namely AutoMap (K.M. Carley, D. Columbus, et al., 2011) and ORA (Kathleen M. Carley, et al., 2011). These tools are publicly available and are also described herein as needed. I explain the D2M process at its current state, and how it is used in this chapter.

The D2M process starts with text data collection:

1. Collect a text corpus (described in section 5.2.1).
2. Clean the text corpus (described in section 5.2.1).

The next set of steps in the D2M process is designed for extracting relational data from texts. These steps involve various pre-processing routines, which are further explained in the next section, and are provided in AutoMap:

3. Create thesauri and/ or adapt existing standard and domain thesauri such that they are appropriate for the given research question, domain and dataset.
4. Review and revise thesauri.
5. Extract meta-networks from the corpus.
6. Review the network data and based on that, revise the thesauri.
7. Recreate meta-networks from the corpus.
8. Iterate until network data seem appropriate.

Once these steps are completed, the extracted data are post-processed in ORA to add geo-spatial information to the extracted networks (step 9). Next, network analysis is performed on the data (10). Then, analysts use the results to suggest potential interventions (11). Finally, simulations are run on the data to explore what-of scenarios and potential interventions (12).

For the application scenarios presented in this chapter, I perform steps 1-8 and 10 as they are relevant for the purpose of this chapter.

5.2.2.1.1 Thesauri: Background, Usage and Construction

The key resource needed for extracting meta-networks with the D2M process are thesauri. A thesaurus, in its simplest form, is a table with two columns that associates text-level terms (first column) with concepts (second column). When applying a thesaurus, the text data are searched for the terms listed in the thesaurus, and any match is replaced with the respective concept. In order to build thesauri, a combination of data-driven NLP techniques, given external resources such as gazetteers, and previously generated thesauri is typically employed. In AutoMap, the NLP techniques available for this purpose include the identification of terms (unigrams and bigrams) with high absolute and weighted frequencies (Diesner & Carley, 2004), and the automated detection and classification of nodes (Diesner & Carley, 2008a). Some of these techniques are computer supported, i.e. they require manual steps, while others are fully automated. For example, before the prediction models presented in chapter 3 were added to AutoMap, the process for detecting multi-word units involved generating a bigram list, which contains all adjacent pairs of words and their cumulative frequencies. The disadvantages with this approach were that the output had to be screened by a person for meaningful two-word units, and the detection of longer units was not supported.

A thesaurus can be used to normalize data as shown in the examples in the next paragraph, or as a positive list or filter, which means that all text terms not occurring in the thesaurus are dropped from the text data. More specifically, in text coding, a thesaurus serves four main purposes, which may overlap:

First, it converts explicit literal mentions of concepts into those concepts, e.g. “cocoa beans” into “agricultural_crops”. Used in this way, a thesaurus represents a taxonomy, which classifies terms into concepts. Second, a thesaurus supports coreference resolution by mapping different spellings, variations, and synonyms of a concept to one consistent key identifier of this concept. For example, “Al-Bashir”, “Omar el Bashir”, and “Omer Hassan Ahmed al-Bashir” can all be mapped to “Omar_al_Bashir”. Third, a thesaurus helps to disambiguate terms. This works for terms where capitalization signals a difference in meaning (capitonyms), e.g. “rice” (crop versus person with that last name). Disambiguation via a thesaurus can also be achieved for terms that have the same spelling but a different meaning, i.e. homographs, which include homonyms, heteronyms, and polysemes. However, disambiguating homographs via thesauri is only feasible if and only if the embedding of the term into the context of a short phrase is sufficient for differentiating the meaning, e.g. “upper arm” versus “arm dealer”. Forth, a thesaurus can be used to convert n-grams into unigrams. This is typically done by replacing the spaces between the constituents of an n-gram with an underscore, as shown in the examples in this paragraph.

Thesauri that are more advanced than the basic two-column data structure contain additional columns that specify the type and further subtypes and attributes of entities. I herein refer to these additional pieces of information on an entity as “categories”. For instance, “Omar_al_Bashir” might be categorized as an entity of the type “agent” with the subtypes “specific” (in contrast to “generic”) and “political”. Thesauri that associate terms with categories allow for text coding and subsequent analysis on multiple levels of aggregation, and also for more fine-grained analysis and filtering.

Traditionally, thesauri have been created by reading through some (Glaser & Strauss, 1967) or all (Gerner, et al., 1994) of the text data to be analyzed in order to identify the terms relevant for a given project, and associating them with concepts and categories. Sometimes, the relevant concepts can be predefined, e.g. if they are derived from theory or when a taxonomy is used. Various computational solutions exist for assisting the user in this task; many of which have been developed for qualitative text coding according to the grounded theory methodology (Lewins & Silver, 2007), and for event coding in the political sciences (Gerner, et al., 1994).

Thesauri are typically created through an iterative process of testing and modification. Sometimes, external resources can be used to build or extend a thesaurus. For instance,

Appendix A of the CIA World Factbook lists acronyms commonly used for various organizations, such as “WHO” for “World Health Organization” (Central_Intelligence_Agency, 2009).

There are two main advantages with thesauri: First, they allow for working with a controlled vocabulary. Second, they support the consideration of subject matter expertise for text coding. This means that while experts are able to define terms that represent relevant concepts in a domain, and also to categorize terms, these concepts and categorizations might not be retrievable with statistical NLP techniques.

Thesauri involve several limitations: First, they can be outdated, incomplete, insufficiently discriminating between the different meanings of terms, and not contain the typos occurring in real data. The deterministic nature of a thesaurus can be improved by not only searching for hard matches, but also for soft matches in spelling via string similarity algorithms (Cohen, Ravikumar, & Fienberg, 2003). Second, since thesauri are typically built for specific domains, genres, or datasets, they can be expected to perform less accurately on new corpora. Finally, building thesauri is very costly in terms of effort and time, especially when a thesaurus is built by hand or in a computer assisted fashion.

5.2.2.1.2 Construction of Sudan Master Thesaurus

For this study, I am using a thesaurus herein referred to as the Sudan “master thesaurus”. This thesaurus was built by various members of CASOS over multiple years by integrating multiple thesauri previously built at CASOS and elsewhere, enhancing the resulting file with the D2M process in AutoMap, and repeatedly cleaning and enhancing the thesaurus. These steps were mainly conducted by individuals other than me inside and outside of CASOS, and no complete documentation exists for this process. Therefore, I consider the master thesaurus as a given input.

This section describes how I refined and enhanced the Sudan master thesaurus. Out of the different thesauri that I built for this chapter, the Sudan master thesaurus required the most amount of effort for cleaning and manual validation. The resulting thesaurus can serve as a starting point for building thesauri that can be used for analyzing data about other geo-political entities and other news wire corpora, which is a main application domain for thesauri in CASOS. For these two reasons, I use this thesaurus not only for this application scenario, but did also use it as a look-up dictionary for constructing the prediction models in chapter 3.

I want to mention two particularly important thesauri that had been previously integrated into the master thesaurus: first, the counter-terrorism agent thesaurus (CT agent thesaurus) is a collection of entities of the type “agent” that are relevant in various counter terrorism contexts. This file has

been constructed and verified by subject matter experts (Gerdes, 2008) and accounts for 20.6% of all agent entries in the master thesaurus. Second, the rapid ethnographic retrieval (RER) thesaurus was built by our project partners at East Carolina University. This file associates terms with concepts that subject matter experts have identified as being crucial for answering questions about the culture of groups and societies. These terms associations result from both, theory and empirical work in anthropology and sociology (K.M. Carley, M. Lanham, et al., 2011). Many of the RER terms are based on the "Human Relations Area Files" (HRAF), which are a classification schema for information about human behavior and culture, and are widely used in anthropological analyses. The RER thesaurus provides 2.7% of the entries in the master thesaurus.

All terms and concepts in the master thesaurus, except for a list of about 13,000 universities, are in lower caps. This eliminates the need to enter terms twice if they can occur either way, but at the same time disables the possibility of word sense disambiguation of capitonyms.

The version of the master thesaurus that I use is from May 25th, 2011. Towards the end of the cleaning and refinement process described in the following I was given an updated RER thesaurus with entries for the task, resource and knowledge class, and a list of about 13,000 universities that are classified as organizations with the subtype "educational. Integrating these files with the master thesaurus required repeating all cleaning steps for these two files, and deduplication all impacted entities classes again. The numbers presented in this chapter are adjusted for these additional steps. This limitation to efficient scientific work reflects the nature of practical text coding applications: thesauri are ever evolving tools that need to be adjusted for time, domains, and writing styles, among other criteria.

The master thesaurus has seven columns: the "terms" (229,998 lines), one "concept" per term, the "meta-network category" that the concept maps to (for 99.4% of the concepts), a "subtype" per concept (for 14.7% of the concept), and the "city", "state" and "country" for the entries from the university file where available. Table 86 shows the distribution of terms across categories. I cleaned and enhanced this file as follows:

First, I used a CASOS tool that helps to remove lines that contain illegible characters in the term and concept column. This tool converts characters from the UTF encoding set to the respective ASCII character while leaving all ASCII characters untouched. Terms removed included "x x•x"x¤x•x§" and "D±N€NƒD½DµN". Those entries resulted from scraping webpages and moving files between different encoding sets without adjusting for the character set. This step reduced the number of lines by 19.5%. Of those lines removed, 97.6% were from the "location" class, and another 1.6% from the "agent" class.

Next, I manually fixed all typos in the meta-network categories (N=107, where N means number of lines). This is important because otherwise these classes would be considered as additional categories. I also removed all entries marked as "ignore" (N=18), which were leftovers from a prior (to this thesis) round of editing.

Table 85: Overview on entries with digit(s) in term values (excluding industry codes, ticker IDs)

Meta network category	Number of entries with digit(s) in term	Number of entries with digit(s) after digit cleaning	After cleaning, entries with digit(s) being relevant	After cleaning, entries with digit(s) being irrelevant
Agent	263	151	22%	78%
Atribute	7	0	0%	0%
Event	89	58	84%	16%
Knowledge	151	86	59%	41%
Location	290	188	62%	38%
Organization	534	307	60%	40%
Resource	148	89	61%	39%
Task	35	42	29%	71%
Blank	10	0	0%	0%
Total	1,527	921	54%	46%

Then, I checked all entries that had an underscore between words in the term column (N=2,751), which are the result of previous issues with merging and deduplicating thesauri. Underscores are only supposed to occur in the concept column and are there to covert n-grams into unigrams. Of those entries, I removed all but those from the RER thesaurus, and fixed the RER entries (171 kept).

At this point, the thesaurus still had several entries that were noise and featured certain symbols. Again, those entries might result from collecting data online and from moving information between different character encoding sets, among other reasons. I manually worked through these entries:

Question marks (N=569): I vetted 14 of them as useful and unproblematic; most of which were speech acts and abbreviations used in web talk, such as "wuf?" (an abbreviation for "where are you from?"). I fixed another 38 by removing the question marks, and removed the rest as they were noise.

Quotation marks (N=480): I kept 48 of those entries; some of which needed some manual fixing. The rest was dropped because they were also noise. The maintained entries are from the "agent" class, such as "haji neamatullah "shirdai" khan", and terms representing universities, such as University ""Dzemal Bijedic" of Mostar".

Digits: When the D2M process is used to retrieve potentially relevant entities from text data, digits are removed from the entities as those entities are often considered as noise. Since we had no data on how appropriate this strategy is, I went through all entries in the thesaurus that contain a digit in the term (N=3,012). Of those, 49.5% are industry codes, e.g. "naics111140 wheat farming", and news ticker IDs, e.g. "9501 (tse)"; both of which I did not attend to. Out of the 1,527 remaining ones, I vetted 39.7% as noise and dropped them, 32.6% as relevant and correctly formatted, and 27.7% as relevant yet problematic. I fixed the problematic cases, e.g. by removing the digit from the term or changing the meta-network category. All entries that I did attend to were added back into the master thesaurus. Table 86 shows that digits are a meaningful constituent of more than 50% of the entries that comprise digits (excluding industry codes and ticker IDs), such that dropping them entirely would cause of loss of information.

In total, the handling of the entries that contain certain symbols shows that 90% or more of the terms comprising question marks and quotation are noise, while digits are a relevant component of about every other impacted entity.

After the symbol handling was done, I manually defined concepts and meta-network categories for each unlabeled term (N=1,024). There is no explicit code book that would guide this process, but several guidelines (K.M. Carley, D. Columbus, et al., 2011) and plenty of norms have been established in the CASOS center for this process. I adhered to these norms, built upon my experience with plenty of previous text coding project in CASOS, and double checked on cases I was uncertain about with the director of CASOS, Dr. Kathleen M. Carley.

Next, I worked through the entries in each entity classes individually. Doing that for the agent class took the most effort, and the steps required there do not necessarily generalize to the handling of the other entity classes. Therefore, I describe this process separately, followed by a general description of problems and solutions for the other nine entity classes.

5.2.2.1.2.1 Agents

Most of the problems for the agent entries were cases in which instances of "roles" were lumped together with reference to specific agents, such as "president omar al-beshir". Also, for all agents, we want to be able to distinguish between specific (omar al-beshir) versus generic (president) instances. However, of the 29,690 agent entries, only 1,789 (6%) were marked as "specific", and 30 as "generic"[14]. Moreover, instances of "roles" and "generic agents" mainly overlapped. Another minor issue with the agent class was that several concepts contained spaces, which I replaced with underscores.

[14] Two more agent entries had the subtypes "corporate" and one as "non-corporate".

In order to split up entries composed of generic and specific references to agents, and to classify all entries into either one sub-type, I started by manually reviewing the existing CASOS roles file. This file has 741 entries. I decided to remove 18 of them, mainly because they often occur as part of proper noun phrases, i.e. specific agents, e.g. "khalif". I built a tool that applies the roles file to the terms and concepts column of a thesaurus; separating roles from specific agent representations per line and column. Next, I went through all agent entries and took everything that did not represent a specific agent out into a separate file (delete list). This delete list contained 2,820 entries, some of which were additional roles, and others were noise.

Several types of conflicting cases were less straightforward to handle: some instances of roles are often part of proper names, e.g. "pope" ("pope john paul"), "father" and "prophet" in a religious context, or "khalif" and "khalifa", e.g. Ayad Futayyih Khalifa al Rawi. Removing the role from the name would not allow for mapping this name anymore to the text data, but might still be helpful for cleaning up other names. Also, some roles overlapped with common proper names, such as "king" in "martin luther king", where removing "king" would also alter the proper name in an undesired way. Furthermore, some roles coincide with common nouns and noun phrases, such as "west" in "allen west", where mapping every instance of "west" in text data to this particular agent would most likely be wrong. For these scenarios, I made decisions based on which usage of a term (role or any other) seemed more common for news wire data. Applying the resulting extended delete list to the agent entries did impact 34.9% of the terms, 12.8% of the concepts, and 35.4% of all agent entries. Out of all term-concept pairs that were subject to this process, 6.5% were reduced to empty pairs. It is noteworthy that only 8.6% of the entries from the CT agent thesaurus were impacted by the role removal process, which indicates that these entries had already been subject to cleaning procedures and consistency checks.

In general, in AutoMap, once a thesaurus has been constructed or changed, co-reference resolution has to be performed on the thesauri in a manual fashion. This involves mapping synonyms to a unique node name. Also, since AutoMap does not yet disambiguate terms based on capitalization or parts of speech, one has to decide which meaning of a capitonyms and homographs to assign to all instances of these words, e.g. whether to code "rice" as a person in the sense of the politician or a resource in the sense of food. The master thesaurus supports reference co-reference resolution by associating different variations of a name with a unique spelling of that name. Several pseudonyms, aliases and noms de guerre are also handled by the thesaurus. Since the cleaning routine described above had impacted the terms and concepts, the co-reference resolution had to be redone. In fact, both, the CT agent file as well as the other agent entries contained cases where one term was mapped to multiple concepts in the original

master thesaurus. I iteratively developed and implemented a rule-based approach to solve this problem:

- All comparisons are performed on the level of exactly matching letter and numbers, but not symbols.
- For all cases in which multiple occurrence of one term map to more than one concept, the concept from the CT agent file is used if the term occurs in the CT agent file, otherwise the most frequent concept is used.
- In the case of a tie, the term that first occurs in the alphabet is used.
- For unigrams, I apply additional rules: conflicts for unigrams occur if one part of a name is mapped to multiple combinations of a first name and a last name. For first names, it is hard to tell which full name it is to be associated with. Therefore, unigram terms are associated with the concept from the CT agent file if the unigram occurs only once. Otherwise, the unigram is translated into itself.

Next, I deduplicated all agent entries by removing those entries that were identical in term and concept. The deletion and co-reference resolution process had caused several terms to become very short, which implies the risk of mapping a meaningless or overly common term to an agent, such as "john" (unclear which "john" is meant). I reviewed all terms and concepts of length four and less (N=686), and removed 27 of them as they were noise. During this process, I found ten more terms that had been reduced to just roles. I removed those lines, but did not add the roles to the role file since those term represented some of the difficult cases described earlier.

Next, I manually classified all entries in the role file as a meta-network category unless they were noise terms. Most of them were assigned to agent of subtype generic or to attributes.

Finally, I checked the agent file against a list of tribes in Sudan, and removed one matching entry from the agent file ("subayh"). This would have been a false positive in the agent class.

5.2.2.1.3 Using the Master Thesaurus for Extracting Meta-Networks

Once the Sudan master thesaurus was built, I used it as part of the the D2M text coding process in AutoMap. Since the text corpus and thesaurus are sizable, I used the script version of AutoMap for processing. With this version, the user fills out a script that specifies the coding choices and input and output directories.

In order to choose appropriate coding choices for this project, I drew from the knowledge gained in chapter 2, and from consultations with other members in our group who were also processing the Sudan corpus and other text data sets about large-scale, geo-political entities. I selected the following coding choices:

- *Cleaning of all texts*: this routine deduplicates texts, removes meta-data, corrects types by applying a thesaurus of common typos, and expands contractions and abbreviations by using thesauri.
- *Thesaurus application*: the master thesaurus described in the previous section was applied such that only entries matching the thesaurus are kept in the data (thesaurus content only option) while maintaining the original distances between concepts (rhetorical adjacency option). Comparisons between text terms and thesaurus entries are performed on a lower case basis. All concepts in the output data are also in lower case.
- *Meta-network extraction*: AutoMap uses the windowing technique for link formation. The parameters taken into account for window-size specification include the text unit, such as sentence or paragraph, and the number of words. Based on the experimental results and respective practical implications for appropriate window sizes from chapters 2 and 4 of this thesis, I used a window size of seven. Also, I allowed for the windows to span across a sentence. In order to address the potential risk of finding false positives, I coded roles and attributes not as instances of node classes, but as attributes of nodes from other classes.

The output from this process are directed, weighted graphs that are output in DyNetML format (Kathleen M. Carley, et al., 2011), a XML format developed for describing graphs. One DyNetML file is output per input text file. In the next step, I consolidated these outputs as follows: all file that were published in the same calendar year were aggregated into one DyNetML file per year. This requires that each filename contains the time stamp from the article in a specific format (yyyymmdd). I used the publication data of articles as the timestamp. A limitation with this approach is that the actual event may have happened prior to the publication data. Each resulting DyNetML file represents all the nodes and edges that were found in all if the text files per year. If a node or edge were found more than once, their initial weight of one is increased accordingly. Once this process was completed, the DyNetML files were loaded into ORA.

Inspecting the network data files in ORA showed that many nodes still appeared as multiple mentions, i.e. they represent the same entity, but have different node IDs and thus occur as multiple nodes. For instance, there were still 18 different nodes that all represented Omar al-Bashir. I used the following strategy for conducting another round of co-reference resolution, now on the node level: first, I loaded and applied attribute files that assign a specificity value to nodes where available. I had built these attribute thesauri as part of the master thesaurus, and also for my previous work on coding the Sudan data. Except for the agent class, these thesauri did not cover all nodes in the networks. Therefore, I labeled all nodes from the organization class that

had a frequency of 1,000 and more in the union of all annual networks with a specificity value. The number of 1,000 was chosen as an artificial cut-off point. Ideally, one would want to assign a specificity value to all entities, but since this process has to be done manually, such procedure would not be feasible for a single person in a reasonable amount of time. Next, I selected all agents and organizations with the specificity value "specific", and for each of these nodes with a total occurrence of more than 1,000 times, I checked if they can be merged with any other node from the same class and of any frequency, including frequencies of less than 1,000. The resulting node merging lists can be stored, but needs to be applied to every network and node class individually in ORA. In total, just the process of assigning specificity values and conducting co-reference resolution on nodes took about four work days.

In summary, in comparison to the original agent portion of the master thesaurus, the reworked portion contained 19.5% less unique agents and term-concept pairs (N=23,832), and 5.0% less unique concepts (N=19,387). All remaining unique agents are specific ones - an increase by 22,043. Preparing the agent entries of the master thesaurus involved several limitations:

First, terms that represent generic as well as specific agents were not removed from the file in order to not to lose this information altogether. An example would be "christian", which can be a first name or a person that adheres to the Christian religion.

Second, translating unigrams into themselves causes a loss of precision in some cases, while in others, it avoids the mapping common first names (paul, bill, mark) or common other words (ban, rice) to one specific agent.

Third, terms that only differ in symbols are not considered as being identical, such as "hassan yemen al-rabiai" versus "hassan yemen al rabiai". I chose this rule because differences in symbols often also signal different agents, or would conflate a term with a non-agent term, such as "sa-id" and "sa'id"; both of which are common first names.

Forth, the co-reference resolution approach is not optimal and incomplete. On average, each agent concept in the final master thesaurus maps to 1.2 terms. For example, "omar hassan al-bashir" is mapped to "omar_al_bashir", while "omar hassan ahmad al-bashir" is mapped to "omar_hassan_ahmad_al_bashir", even though many variations of this name are collected together under the latter and more common spelling. The rule based consolidation approached used herein can only partially alleviate those issues. Moreover, in many cases, it is not obvious if two similar names really represent the same person. Further resolving this limitation would require subject matter expertise and more manual work.

While the first three limitations are classic caveats of rule based systems, the forth one is a known shortcoming of thesauri. Furthermore, the first two limitations are specific to the agent

entries, while the last two limitations also apply to the cleaning of other entity classes, which is described next.

5.2.2.1.4 Limitations of Working with Thesauri

In general, the manual and semi-automated verification and correction of a thesaurus as demonstrated in this section serves the validation of a thesaurus and the improvement of the quality of the thesaurus. However, working with thesauri involves several limitations, which are described in the remainder of this section. These issues are mainly due to the fact the master thesaurus was built, maintained and extended over years by multiple people and teams from multiple sources, which is a realistic and common scenario.

Working through the remaining nine entity classes (organization, location, resource, knowledge, task, event, time, belief, attribute) revealed several common issues. These issues are mainly due to the following reasons. These problems and limitations may overlap.

- Homonymy of terms and concepts.
- Gathering of data from external sources, such as the web (potentially messy) and structured databases (more clean).
- Integrating of information from various research groups, such as the cultural indicators (RER) from ECU with the CASOS thesauri.
- Pre-processing of the text data prior to thesaurus construction.

After summarizing the main issues, I next describe some of the problems in more detail.

First, concepts considered in the thesaurus are sometimes represented by very common terms ("conflict" by "against"), or by terms that have another meaning which is more frequent, but not intended with the thesaurus entry ("well" coded as "water"). These two problems were solved by removing overly common terms from the thesaurus, such as "go", "take", "will" (intended sense was a declared intention) and "me" (personal pronoun and abbreviation for the state of Maine).

The second issue results from AutoMap coding every distinct term into only one concept; with ties being broken alphabetically. This is problematic for terms that map to more than one distinct relevant concept, such as "fur" to one of the main tribes in Sudan as well as to the natural resource. The same problem applies to acronyms and abbreviations which represent multiple entities. In these cases, I chose the anticipated more frequent meaning in the context of the text corpora used herein.

Third, various concepts appeared in multiple meta-network categories, such as the "oslo accords", which is short for the "Declaration of Principles on Interim Self-Government

Arrangements", and was coded as knowledge (in the sense of a document) and event (in the sense of the meeting itself). For these cases, I developed data-driven rules that I adhered to.

In total, the master thesaurus contained over 1,000 conflicting cases where the same term was assigned to more than one concept, or the same concept assigned to more than one categories. Resolving these issues required working through them on a case by case basis. For some homonymous terms where the different meanings (concepts) were each highly relevant, the less common meaning was eliminated. For instance, I dropped "turkey" coded as "livestock" in order to keep "turkey" coded as a location. Some term to concept assignments were kept since they occurred frequently with the intended meaning in the corpora I use, e.g. "general" as a military rank, but these assignments might not be appropriate for other datasets. Furthermore, decisions on several terms required substantial subject matter expertise. For example, there were several hundred terms coded as a person and an organization (e.g. "wazir"), or as a person and a location (e.g. "bahr el ghazal"). For these cases, the most appropriate assignment was not obvious to me. Resolving these issues required substantial additional research.

Fourth, many terms that were picked up by automatic entity extraction techniques when building the thesaurus contained irrelevant words in addition to the relevant ones, such as verbs as well as the names of months and days of the week as part of noun phrases. I removed those when I found them and where it seemed appropriate.

Fifth, several sections of the master thesaurus were retrieved from external webpages. In general, extracting relational data from the web has become a useful and popular strategy for filling relational databases (Cafarella, et al., 2006). However, scraping the web for collections of terms and concepts can result in the retrieval of large numbers of additions to the thesaurus, but these entries include noise that requires further inspection and cleaning. For example, many of the locations were collected from resources that include the foreign translation of location names, which coincide with common English terms.

Sixth, the creators of different thesauri had not always used the same guidelines for associating terms with concepts. For instance, the RER thesaurus often codes roles as resources, such as "laborer", while the CASOS role file considers them as roles. Also, the RER thesaurus considers diseases as knowledge, which would be appropriate in the context of research papers, while the CASOS thesauri consider them as a resource, i.e. something that one can acquire. Since the RER thesaurus was built by experts, it was given precedence in most cases. Many of these conflicts have no right or wrong solution to them. The choices made are based on norms and guidelines specific to an organization or a field, and on the context of the text data to which the thesauri are to be applied.

Seventh, the master thesaurus includes stemmed versions of terms. The problem with that is that some morphemes coincide with other common English terms. This issue particularly applied to location names that were retrieved from external digital resources. Also, the stemmers that were used are designed for English text data (Diesner & Carley, 2004), such that errors on applying them to foreign words are to be expected.

After reviewing the entries per entity class and correcting for the outlined issues where possible, the revised master thesaurus required performing disambiguation and deduplication again such that some of the issues outlined above had to be addressed again. I also kept one thesaurus per entity class since those contain more entries than the consolidated master. In order to test the quality of the revised master thesaurus and to check for further noise terms and inappropriate associations, I applied the thesaurus to the Sudan corpus as follows: I generated a term distribution list that specifies the cumulative, observed frequency of each term and concept, and how many texts they occur in. I inspected all occurrences with a frequency of 1,000 and higher (N=1,607), and fixed all problematic entries. Repeating this process one more time and inspecting the thesaurus afterwards suggested that the quality of the thesaurus was sufficiently high at this point.

Overall, the thesaurus cleaning procedures had major impacts on the master thesaurus as summarized below. Table 86 further provides a quantitative overview on these impacts.

- The number of entries in the master thesaurus was reduced by over 26%. While some classes are reduced by even larger ratios, the role class and to a lesser degree also the attribute class were extended.
- Over 43% of the entries in the master thesaurus were changed in one or more column. This means that the qualitative effect of cleaning the thesaurus is larger than the quantitative impact.
- More than 76% of the entries in the revised file were taken from the original file with no changes, but this ratio differs widely depending on the entity class: in fact, for six out of the ten classes, more than 85% of the entries in the revised file are from the original file. This means that while large numbers of entries were dropped from each original class, the remaining original entries make up the bulk of the entries in the revised class. However, for the classes of agent, attribute and role, almost all entries got changed or added after dropping noisy and erroneous entries.

Table 86: Size and categories of master thesaurus, original and revised

Meta network category	Number of entries in master original	Number of entries in master revised	Change in number of lines from original to revised	Number of lines identical between original and revised	Entries in revised retained unchanged from original	
					base: original	base: revised
Agent	30,822	24,160	-22%	995	3%	4%
Attribute	669	768	15%	0	0%	0%
Belief	268	271	1%	260	97%	96%
Event	1,898	1,665	-12%	1,633	86%	98%
Knowledge	5,741	4,621	-20%	4,142	72%	90%
Location	147,885	101,163	-32%	100,458	68%	99%
Organization	32,232	29,199	-9%	17,240	53%	59%
Resource	5,631	2,345	-58%	2,005	36%	86%
Role*	73	1,946	2566%	42	58%	2%
Task	3,647	3,653	0%	3,267	90%	89%
blank	1,024	0	-100%	0	0%	0%
wrong categories	108	0	-100%	0	0%	0%
Total	229,998	169,791	-26%	130,001	57%	77%

* in revised: agent generic

Two more limitations apply to the thesaurus revision process: First, all cleaning and rule creation described herein was done by a single person (me) in consultation with the people involved in handling our thesauri and my advisor. Any errors that I did not spot remain in the data until somebody else finds them.

Second, building, refining and extending thesauri is very costly in terms of time and human effort: working through 500 lines took about one hour on average for most of the processes described here. Altogether, revising the master thesaurus took me about six work weeks. Adjusting the master thesaurus to another dataset or domain, or building an entirely new thesaurus, is likely to involve significant time costs of several days, weeks or months. However, once this work is done, using the thesaurus is efficient: the total time costs for coding texts as networks in AutoMap and consolidating the files as described in this section were about a day and a half. Using the revised master thesaurus as is will not increase time costs beyond the processing needed for AutoMap. Moreover, in AutoMap, a plethora of previously generated thesauri are provided to end users. Those are general thesauri that handle the conversion from British to American English, expansion of contractions and common abbreviations.

5.2.2.2 Network Data Extraction from Texts Using the Data to Model Process and the Entity Extractor

The same process for generating network data with the D2M process as described in the previous section was repeated with one change to it: I replaced the Sudan master thesaurus with a thesaurus generated by applying the entity extractor developed in chapter 3 to the Sudan corpus. I refer to this thesaurus as the auto-generated thesaurus. Inspecting the auto-generated thesaurus and a first batch of network data generated with it suggested that the auto-generated thesaurus cannot be used as is to retrieve quality network data, but also needs further cleaning. However, this thesaurus featured different issues than the Sudan master thesaurus, such that different strategies were needed for handling them. Thus, I refined the auto-generated thesaurus as describe below. This description might also serve others who use the entity extractor in AutoMap to covert the raw, suggested thesaurus into a quality text coding tool.

Refining the auto-generated thesaurus was an iterative process: I implemented a change, used the modified thesaurus to generate network data using the same process as described above in section 5.2.2.1.3, inspected the thesaurus and the network data[15], made further changes to the auto-generated thesaurus, and repeated this process. The steps described in this section are not all of the changes I tested, but those that I assessed as being effective and leading to the intended improvements without causing unintended side effects. Also, I tried different orders in which these steps are applied. The sequence of routines described in this section is the ordering that led to the best quality of the auto-generated thesaurus.

For thesaurus generation, I used class model 4, which outputs a class label, specificity value, and subtype value for each identified entity (for details on the class models see chapter 4) . The output file further contains the part of speech for each constituent of an entity, and the frequency with which an entity (case-sensitive) with the same class label, specificity value, subtype and part of speech has been identified in the text data. The auto-generated thesaurus had 502,485 unique, regular entries with a cumulative frequency of 5,380,091, and another 28,922 additional suggestions (for details on the additional suggestions see chapter 4). Since the number of regular entries was already large, many of the additional suggestions were already contained in some form in the regular entries, and many of the additional suggestions seemed only tangentially relevant, I decided to disregard them from the auto-generated thesaurus.

In order to assess the quality of the auto-generated thesaurus in a practical application setting, I manually reviewed the suggested entries per category (total of 44). Table 87 lists these categories

[15] Since the thesaurus format in AutoMap accepts one attribute per entity, I stored the additional attributes (subtype, parts of speech value) as separate files and added them into the DyNetML files in ORA.

along with their accuracy obtained during k-fold cross-validation, which serves as a point of comparison here (for details on formal model evaluation see section 3.4.7). The table also contains the cumulative sum of retrieved instances per class, and my assessment of the prediction accuracy per class in the application context. I performed this assessment in a qualitative way: I screened the entries per class; especially those with high frequencies, and categorized each class as having good, medium or bad prediction accuracy in the application domain. Ultimately, such an evaluation should be performed by multiple people to avoid intra-coder reliability issues and biases. However, this first evaluation serves two purposes: first, to identify general issues with the auto-generated thesaurus, and to understand how they relate to issues identified for the master thesaurus built in the previous section. Second, to understand which issues are corpus specific, and which generalize across the application scenarios.

Table 87: Application of prediction model to auto-generate thesaurus for Sudan corpus

Class labels	**K-fold cross validation**	**Application to Sudan data**	
Meta-network category, specificity, subtype	Accuracy	Size: Number of examples in thesaurus	Assessment of quality
resource, na, money	97.7%	28,757	good
location, specific, country	97.0%	606,204	good
org-att, specific, nationality	93.8%	145,578	good
attribute, na, numerical	93.4%	394,769	good
time, na, na	93.4%	396,072	good
event, specific, war	92.6%	2,280	good
agent, specific, na	92.3%	200,658	bad
organization, specific, gov.	90.8%	136,919	good
org-att, specific, political	90.5%	807	good
agent, generic, na	90.2%	882,345	good
organization, generic, corp.	88.7%	283,014	good
location, specific, city	88.1%	157,603	good
organization, specific, corp.	87.2%	854,630	medium
location, generic, country	87.1%	126,048	good
location, specific, state-prov.	85.4%	7,059	good
organization, generic, gov.	81.4%	71,840	good
organization, specific, edu.	77.8%	15,645	good
location, generic, city	77.7%	24,098	good
knowledge, specific, law	77.5%	48,340	good
organization, generic, edu.	72.7%	5,826	good
location, specific, other	71.8%	34,687	good
resource, generic, product	71.7%	96,935	good
event, specific, na	69.0%	9,917	medium
location, generic, facility	67.9%	60,165	good
organization, specific, other	67.1%	155,225	good

attribute, na, age	66.9%	37,860	good
organization, specific, political	63.8%	15,408	good
resource, na, substance	62.0%	36,810	good
organization, generic, other	61.6%	67,556	good
org-att, specific, religious	59.6%	2,517	good
location, generic, state-prov.	52.9%	34,354	good
resource, na, disease	50.8%	9,944	medium
knowledge, specific, language	50.0%	3,484	good
location, specific, facility	49.8%	35,929	medium
knowledge, specific, art	48.5%	312,947	bad
organization, specific, religious	48.5%	15,896	good
resource, na, plant	48.5%	2,918	good
organization, generic, political	48.3%	469	good
organization, generic, religious	47.1%	4,238	good
resource, na, animal	40.4%	8,598	good
org-att, specific, other	34.4%	15,621	good
task, na, game	29.6%	378	good
resource, specific, product	28.0%	26,968	bad
location, generic, other	18.8%	2,775	good

During this assessment, I made the following observations:

First, overall, many of the suggested entities and category assignments seemed relevant and correctly labeled.

Second, some categories were particularly error-prone. Most of those errors were cases in which relevant entities were picked up, but assigned to the wrong category. Especially agents with the specificity value "specific" were particularly likely to show up in other categories, mainly as specific knowledge of subtype art and specific organizations. The latter issue was also observed with the master thesaurus, where deciding on the right category required substantial subject matter expertise. Furthermore, most of the categories that performed poorly in the application domain had also shown low performed during k-fold model evaluation (see Table 87). Three classes had an overall low accuracy and were not absolutely needed for further analysis, and were therefore removed altogether:

- knowledge, specific, art (rank during k-fold cross validation: 35 (lowest =44))
- organization, specific, product ((rank during k-fold cross validation: 43)
- resource, specific, product (rank during k-fold cross validation: 13)

Also, I removed commas from the retrieved concepts to ensure that the thesaurus complies with the csv format. The quantitative impact of this and all other thesaurus cleaning processes described in this section is summarized in Table 90. However, some of the categories that scored low during cross-validation did not deliver poor results in the application scenario. For example,

entries from the category “location, generic, other”, which had the lowest performance with class model 4 during cross-validation, returned reasonable results on the Sudan corpus.

Third, many of the erroneous entries originated from the beginning of sentences. Those were typically common nouns that would not appear in upper case form otherwise. For learning the models, I had included a feature that addressed this situation, and this feature added a meaningful amount of accuracy to the models. Besides potential weaknesses with this feature, there could be other reasons for the observed limitation: the beginning of sentences is also a challenge for the parts of speech tagger, which might further lower the certainty with which common nouns are categorized, and might also dilute the accuracy of classes where most instances occur as capitalized tokens at the beginning of sentences and elsewhere, such as specific agents.

Fourth, further screening the thesaurus suggested that some entries differed only in symbols, e.g. “NGO” versus “(NGO)”. Other entries resembled delete list entries. To solve these issues, I identified a list of irrelevant symbols, and removed them from all entries while maintaining the content of the impacted cells. Next, I applied the same delete list as used for the Sudan master thesaurus to the auto-generated thesaurus. Items were removed only if they exactly matched a delete list entry (hard match on cell level).

Fifth, many entities showed up in multiple categories. For example, “muslims” were categorized as agent, generic, noun phrase (frequency = 4) as well as “organization, specific, religious, noun phrase (frequency = 1,276). Like in the given example, many of these alternative assignments are plausible in specific contexts. It depends on the research question and size of the dataset whether one wants to extract these alternative nodes from the texts or not. However, since the thesauri in AutoMap are not capable of differentiating between entities of the same class in different contexts, I had to remove alternative categorization, and did that by keeping the one with the higher observed frequency count. I built and applied a tool that consolidates nodes according to the rules shown in Table 88. Whenever thesaurus entries are merged onto the same concept based on these rules, the frequencies of these entities are added such that the total cumulative entity frequency remains constant.

Reviewing the auto-generated thesaurus at this point suggested that the highly frequent entries seemed correct to me, and no categories with an overall poor performance were still present. However (sixth), inspecting the generated network data in ORA suggested that many entities still occurred in the wrong meta-network category, and with surprisingly high frequencies. For example, “Dr” occurred as “location, specific, country”, but according to the auto-generated thesaurus, should be an attribute. Further investigating this issue revealed that AutoMap internally converts every entity in a thesaurus to lower case before translating text terms that

match thesaurus entries. This is troublesome for capitonyms: "DR" is a common abbreviation for the Democratic Republic of Congo, and has a different meaning and thesaurus entry classification than "Dr", which truly is a personal attribute. I realized that if a term appears as capitalized as well as in lower case, AutoMap by default and without an option to change this behavior picks the lower caps term. Consequently, both "Rice" (the person) and "rice" (the food) are categorized as a resource of subtype substance, and the same is true for "Bush" versus "bush" and "Apple" versus "apple". Since this feature was not up for change, I extended the thesaurus entry consolidation tool described above such that it also merges terms that have the same spelling regardless of capitalization. In this tool, the category assignment of the term with the higher frequency is chosen, and the term frequency is increased accordingly.

Table 88: Entity consolidation in auto-generated Funding thesaurus based on matches in certain features

Consolidation based on	**Consolidated if entities match in:**					
	Spelling (case-sensitive)	Meta-network category	Specificity	Subtype	Ratio of unique entities reduced	Ratio of unique entities reduced
POS	x	x	x	x	1.4%	0%
Subtype	x	x	x		3.1%	0%
Specificity	x	x			0.9%	0%
Meta-nw. category	x				10.7%	0%
Word identity					4.6%	5.8%

Seventh, further reviewing the thesaurus suggested that the relevance and accuracy of entries drops as the cumulative frequency of entries decreases. More specifically, at low frequencies, entries tend to become long chains of multiple revenant entries, e.g. "the Sudan Liberation Movement (SLM) faction of Arkoi Minawi". Typically, we are interested in representing these entities (in this case SLM and Arkoi Minawi) as separate ones. Splitting up those chains is also important as AutoMap maps text entries to the longest (in terms of number of tokens) concept it finds in the thesaurus, such that long chains will take away matches from shorter, more relevant entities. Therefore, I removed all entries with a frequency of less than three, since three seemed an appropriate cut-off point for this thesaurus.

To further assess the quality of the thesaurus, I reviewed the entity class, specificity value and subtype of all entries with a cumulative frequency of 500 and more (N = 807). These entities account for only 2.09% of all unique entities in the current version of the thesaurus, but for 78.1% of the total entity frequency. I made corrections to the meta-network category, specificity value, or subtype of 39 (4.8%) of these entities. Most of these changes were made to the subtype value, e.g. changing the entities "Doha" and "Eritrea" from "location, specific, city" to "location,

specific, country". This eighth observation indicates that the small amount of entities that make up the majority of the total entity weight are predicted with high accuracy. Table 89 shows the frequency distribution of these entities.

Table 89: Frequency distribution of entities with cumulative frequency of 1,000 and more in thesaurus*

Class	Thesaurus entries unique	Thesaurus entries total	Average no. of repetitions per entity	Ratio in full thes., unique	Ratio in full thesaurus, total
location, specific	143	786,815	5,502	0.37%	22.19%
agent, generic	233	768,531	3,298	0.60%	21.67%
organization, generic	79	350,351	4,435	0.20%	9.88%
location, generic	38	191,804	5,047	0.10%	5.41%
time	87	171,863	1,975	0.23%	4.85%
attribute	64	153,783	2,403	0.17%	4.34%
attribute, specific	29	122,872	4,237	0.08%	3.47%
organization, specific	65	119,098	1,832	0.17%	3.36%
agent, specific	39	35,927	921	0.10%	1.01%
resource, generic	11	22,146	2,013	0.03%	0.62%
resource	11	21,861	1,987	0.03%	0.62%
knowledge, specific	7	14,260	2,037	0.02%	0.40%
event, specific	1	1,861	1,861	0.00%	0.05%
Total	807	2,761,172	3,422	2.09%	77.87%

* four highest values underlined

Next, I manually reviewed the entries in the categories that I had assessed as having medium or bad performance in the application domain, but were not removed from the thesaurus. I corrected the entries with high frequencies.

At this point, I used the auto-generated thesaurus as part of the D2M process to extracted network data from the texts. I unionized the networks per texts into one network per year, and then the yearly networks into one overall network. In this overall network, I reviewed the highly frequent nodes per meta-network category[16], deleted overly common entities, and made changes to the node-class, specificity value, and subtype were necessary. During this qualitative review, I detected three main types of errors (observation number ten):

- Common nouns that would typically occur in lower case appear as upper case terms; mainly because they are the first word in a sentence. Examples are "Equality" and "Referendum". This point is consistent with observation number three.

[16] Entities including and above the following cumulative node frequency values were reviewed: agent, knowledge, location, organization, time, resource: 1,000, event: 100, task: 0. Differences are due to differences in node weight distribution and size of node class; with the "task" class being the smallest.

- All letters in common nouns as well as proper nouns are capitalized, e.g. because the term is an abbreviation or the name of an organizations. Examples are WHO (World Health Organization) and "LOT" (the airline), and TOTAL (the gas company),
- Common nouns as well as word with other part of speech that are typically in lower case are capitalized; mainly because they refer to a named entity with a different meaning. Examples are "Target" (the store) and Nature (the journal).

Instances of all three cases typically occur with a low frequency, and a lower frequency than the more common, lower case version of the those terms. However, since the CASOS tools convert all entities to lower case when applying thesauri and also compare nodes on a lower-case basis, these outlined special cases cannot be disambiguated via capitalization. Instances of these cases were often predicted as specific agents and organizations, but I corrected many of them by moving them to the knowledge and task classes. Also, I decided to delete all instances of the "organization, specific, other" class with an entity frequency of less than ten, since these entries contained too many common nouns. In the future, this problem can be solved by enabling case-sensitivity of the thesaurus routines, and also by disambiguation terms based on their parts of speech. In fact, both types of information are already available in the auto-generated thesauri.

Next, I de-duplicated entities again based on surface form and meta-network category. Also, I performed co-reference resolution on the thesaurus by using the same merge lists for nodes from the agent and organization class as developed and used for the network data generated with the Sudan master thesaurus. Table 91 summarizes frequency distribution of all remaining entities classes across the thesaurus.

Table 90: Summary of thesaurus cleaning routines and quantitative impact

Routine	Entities		Ratio of raw size	
	Unique	Total	Unique	Total
1. Raw auto-generated thesaurus	502,485	5,380,091	100%	100%
2. Remove categories with low performance	283,252	4,115,328	56.4%	76.5%
3. Apply delete list and remove symbols	281,611	3,763,557	56.0%	70.0%
4. Consolidate entries (in named order) based on parts of speech, subtype, specificity, meta-network class, spelling regardless of capitalization	227,309	3,763,557	45.2%	70.0%
5. Remove entries with frequency of less than three	38,632	3,546,065	7.7%	65.9%
6. Correct entries with frequency of 500 and more, correct and clean poorly performing categories	38,617	3,537,234	7.7%	65.7%
7. Correct entries after reviewing high frequency nodes in network data, re-deduplicate nodes	35,629	3,480,330	7.1%	64.7%

Table 91: Frequency distribution of entities classes in thesaurus

Class	Ratio in full thes., unique	Ratio in full thesaurus, total	Average number of repetitions per unique entity
agent, specific	24.8%	4.2%	17
attribute	17.0%	7.7%	44
time	15.8%	8.6%	53
location, specific	13.8%	25.1%	178
organization, specific	10.5%	5.7%	53
agent, generic	6.1%	24.2%	388
resource	4.8%	1.5%	30
knowledge, specific	2.3%	0.7%	29
organization, generic	2.1%	11.7%	529
attribute, specific	1.0%	3.8%	374
event, specific	0.6%	0.2%	27
location, generic	0.4%	5.8%	1,324
task, generic	0.3%	0.1%	22
resource, generic	0.2%	0.8%	382
knowledge, generic	0.2%	0.1%	54
resource, specific	0.0%	0.0%	7
Total	100.0%	100.0%	98

* Ratios of 10% and more in full thesaurus underlined

Reviewed the re-generated network data at this point suggested that the thesaurus is sufficiently correct. I made further refinements to the network data files and the attribute files for the networks in ORA directly, such as changing the node class and specificity value of a few nodes, but did not remove any further nodes.

Overall, this section has shown that the network quality improves if the auto-generated thesaurus if verified and corrected, even though this process involves a substantial amount of labor. However, generating and correcting the auto-generated thesaurus is more efficient than building or cleaning a master thesaurus as described in the previous section, where the thesaurus work took six weeks (5.2.2.1.1): applying the prediction models for inference takes about one hour per one thousand newspaper articles. Further refining the thesaurus, including building additional post-processing tools and testing various (sequences) of refinement strategies, took about two work weeks. Repeating this process in the future will be more efficient as actually shown in the next application case, because parts of this process have now been automated, and a reasonable sequence of step has been identified and tested.

5.2.2.3 Network Data Construction from Meta Data

Meta-data are a type of structured data that are often available when retrieving news articles from archives such as LexisNexis. In LexisNexis, meta-data are conveniently sorted into categories, e.g. "geographic" and "organization". Each category can have zero, one or many entities per articles, e.g. Sudan and Khartoum for geographic. Each entity is associated with a relevance score between zero and one. This score is assigned by LexisNexis without further documentation on this process.

I operationalized link formation between meta-data entities as follows: two entities are linked if they co-occur for the meta-data for an article. This operationalization resembles the notions windowing such that the network data constructed with the previous two text coding methods and those built from meta-data are based on the same notion of link formation. Table 92 shows the mapping that I defined for converting LexisNexis meta-data categories into meta-network categories that ORA can interpret.

The output from this process are bidirectional, weighted graphs. The link weights were computed by using a method developed by Pfeffer and Carley (under review), which basically calculates the average of the minima of the relevance scores for the two entities in each link. When the networks per article are merged into consolidated networks – one per calendar year in this case - the cumulative sum of the weight per link is divided by the number of articles in the corpus per year. Thus, all links have a weight between zero and one, but for frequently observed links, this weight has a stronger empirical support, even though this fact is not visible in the network data anymore. The node weight in the aggregated network represents the number of articles that a meta-data entity had been assigned to.

Table 92: Meta-data categories considered, and mapping to meta-network categories

Category in input data	Assigned to meta-network category
Organization	Organization
Company	Organization
Subject	Knowledge
Person	Agent
Geographic	Location

The advantage with network construction from meta-data is that this process is fast: once the meta-data are downloaded and organized in some structured form, such as a table or database, generating networks this way is basically a data retrieval task, which takes a couple of minutes.

The limitation with this approach is that the assignment of meta-data entries to articles is not transparent as there is no documentation on what algorithm is used by LexisNexis to generate these index terms and their values.

5.2.2.4 Network Data Construction in Collaboration with Subject Matter Experts

I collaborated with Dr. Richard Lobban, who is s a professor of anthropology and African studies at Rhode Island College (RIC) and a leading expert on Sudan, and his team, notably Adam Gerard and Erica Fontaine, on generating this dataset of tribal affiliations in Sudan. The RIC team had provided us with a list of the main tribes in Sudan. I applied this list as attributes to network data that I had previously generated by using the standard data coding process in AutoMap as described in 5.2.2.1 such that some organizations were also classified as tribes. Then, I used ORA to extract the sub-network of tribes, and generated a network visualization of the tribal affiliation network per calendar year. I sent these network visualizations to Dr. Lobban's team, and they marked up the missing nodes and links (false negatives) and invalid nodes and links (false positives). They scanned their maps and sent them back to me, and I made the respective changes to the DyNetML files. We repeated this process until Dr. Lobban's teams considered the networks as representative of the ground truth.

The advantage with this process is that it results in validated network data, which is the only ground truth data that I have available for the Sudan corpus. However, there are also two disadvantages: first, this process is expensive in terms of time and human resources: going through this process took several weeks. This amount of time is comparable to what is needed for constructing or cleaning thesauri. Second, this process does not scale up, and is therefore only appropriate for generating datasets of small to moderate size.

5.2.3 Results

The frequency distributions of predicted entries classes presented in Table 89 and Table 91 (previous sub-section) suggest two points: first, all the classes that I rated as performing medium or badly during application have the value "specific" for the specificity class. Second, the vast majority of all retrieved entities as well as of entities with a frequency of 1,000 or more, which I manually evaluated as being classified correctly to 96.8%, have the specificity value "generic". Taking these points together, I argue that even though network analysis is often focused on named entities; i.e. the network properties, behavior and power of individual people, groups and places, most of the potential nodes contained in text data are references to social collectives, such as types or roles of people and groups. Understanding the impact of such collectives on networks and their participants requires not only performing network analysis on the role or group level, but also considering unnamed entities in addition to named entities in the first place. However,

data on these unnamed entities is often not collected with traditional network data collection methods. Therefore, using entity extraction from text with the approach developed and practically implemented and demonstrated in this thesis can offer a highly valuable addition to classic network data collection methods.

In the results section of this chapter, I refer to the network data generated with master thesauri as D2M networks, to networks constructed with the auto-generated thesauri as D2M+EE networks, and to the networks constructed in collaboration with subject matter experts as SME networks. Reported averages were computed across the networks per year; excluding the union graph, unless specified otherwise.

The size of the networks depending on the network data construction method (Table 93, Table 94) show that even though the auto-generated thesaurus is 4.8 times smaller than the master-thesaurus, the D2M+EE networks have on average about 1.5 more nodes and 1.7 more edges than the D2M networks. Also, 11.5% of the entities contained in the master thesaurus (N=19,489) occur in the D2M networks, while 72.4% of the entities contained in the auto-generated thesaurus (N=25,794) appear in the D2M+EE networks (Table 93). This finding suggests that the auto-generated thesaurus is more effective in the sense that it covers the dataset and domain better than the master thesaurus. However, from a practical point of view, the rate of entities specified in the thesaurus but not in the data is mainly irrelevant: non-matching nodes are disregarded, which has a minor impact on computing time. In summary, since the master thesaurus took three times longer (six weeks) to generate and post-process than the auto-generated thesaurus (two weeks), using the auto-generated thesaurus for text coding as part of the D2M process seems more efficient and more effective.

Both types of networks extracted from the text bodies (D2M, D2M+EE) are larger than the meta-data networks in terms of nodes (D2M: 2.5 time larger, D2M+EE: 3.8), and for the D2M+EE networks also in terms of links (1.4, D2M: 0.8).

In chapter 2.7.2 of this thesis, I had shown that the windowing approach to link identification, which has been used in this application scenario, can lead to a significant amount of false positive links. The networks from the text bodies are subject to this source of error. However, if we assume that the meta-data networks serve as a point for reference for the number of links or graph density, the difference in the amount of links between the meta-data networks and networks extracted from the text bodies is more than three times smaller than the difference in the amount of nodes. The counterargument to this point is that the meta-data networks were also constructed based on co-occurrence; a notion which is resembled in the windowing approach.

In the previous methods section I had shown that not only the master thesaurus, but also the auto-generated thesaurus needs further manual cleaning in order to correct for misclassified entries and to remove overly generic suggestions. Table 94 shows that the number of nodes and edges that get removed due to this process is very similar across the yearly networks (1.6% difference). This result indicates that the number of links does not shrink slower than the number of nodes, which further relates to the potential amount of false positive links, and also suggests a reduced likelihood of this risk. However, it is unclear if the same trend also holds for the opposite direction, i.e. if the number of links grows faster than the number of added nodes depending in the network construction method or not. This relationship is beyond the scope of this thesis, but should be addressed in the future work.

Table 93: Network size per network construction method I

Data	SME		D2M		D2M with EE		Meta-data		Articles
	Nodes	Links	Nodes	Links	Nodes	Links	Nodes	Links	per year
Thes. entries	n.a.		169,791		35,629		n.a.		n.a.
2003	21	15	6,612	142,630	9,932	221,104	4,648	203,274	4,507
2004	26	22	9,894	288,051	14,750	483,862	7,093	441,076	10,059
2005	22	15	9,420	258,502	14,189	434,525	5,765	381,732	7,837
2006	23	27	10,837	345,796	16,313	600,748	3,677	421,896	11,076
2007	23	40	11,195	360,886	16,876	619,204	3,897	465,378	12,243
2008	36	50	10,303	318,721	15,920	539,559	3,374	377,652	10,713
2009	n.a.	n.a.	9,537	294,344	15,024	496,961	2,986	312,228	10,410
2010	n.a.	n.a.	9,378	304,659	15,315	527,851	2,931	294,928	12,543
Union Graph	53	104	19,489	1,130,934	25,794	2,296,397	15,128	1,561,528	79,388

Table 94: Network size per network construction method II

Category	SME	D2M	D2M + EE	Meta-data
Number of node classes	1	8	8	4
Number of networks	1	36	36	16

Table 95: Network size depending on thesaurus cleaning

Data	Raw		Post-processed thes. (step 7)		Ratio of reduced to raw	
	Nodes	Edges	Nodes	Edges	Nodes	Edges
Thes. entries	502,485		35,629			
2003	20,393	498,593	9,932	221,104	48.7%	44.3%
2004	35,092	1,228,551	14,750	483,862	42.0%	39.4%
2005	33,950	1,073,384	14,189	434,525	41.8%	40.5%
2006	41,569	1,448,364	16,313	600,748	39.2%	41.5%
2007	43,994	1,550,240	16,876	619,204	38.4%	39.9%

2008	39,384	1,317,270	15,920	539,559	40.4%	41.0%
2009	36,576	1,204,194	15,024	496,961	41.1%	41.3%
2010	39,791	1,378,412	15,315	527,851	38.5%	38.3%
Union graph	134,507	6,194,467	25,794	2,296,397	19.2%	37.1%

How similar are the networks per network data construction method to each other on a structural level? I answer this question by generating the intersection between any pair of networks from the same years as well as of the unionized graphs, and calculating the amount of nodes and edges from any one type of network that are also present in any other type of network.

The results from intersecting the SME networks, which can be considered as a type of ground truth data, with the other types of networks show that over half of the nodes and over a fifth of the links in the SME network are also present in the D2M network (Table 94). Also, the D2M networks resemble 2.6 times more of the nodes and 3.7 times more of the edges from the SME network than the D2M+EE networks do. This outcome might result from the fact that a list of tribes in the Sudan as identified by our project parents at ROC and ECU (the nodes in the SME network) was also added to the master thesaurus. In contrast to that, all of the tribes listed in the auto-generated thesaurus as specific organizations were identified by the entity prediction models based on the content of the text data only. Furthermore, the intersection between the SME networks and the meta-data networks is zero on the node and link level.

Table 96: Resemblance of ground truth data per network construction method

Data	SME contained in D2M		SME contained in D2M+EE	
	Nodes	Links	Nodes	Links
Thes. entries				
2003	52.4%	13.3%	23.8%	6.7%
2004	46.2%	40.9%	23.1%	9.1%
2005	63.6%	33.3%	27.3%	20.0%
2006	47.8%	33.3%	21.7%	7.4%
2007	78.3%	12.5%	26.1%	5.0%
2008	41.7%	28.0%	11.1%	4.0%
2009	n.a.	n.a.	n.a.	n.a.
2010	n.a.	n.a.	n.a.	n.a.
Union Graph	52.8%	20.2%	11.3%	4.8%

Disregarding the SME network, the intersections between the remaining types of networks are strongest between D2M and D2M+EE; with D2M+EE resembling twice as much of D2M than vice versa (Table 97). Overlaps between the networks derived from texts with meta-networks are small: the text-based networks pick up only a small amount of the nodes contained in the meta-networks (7.8% - 11.5%), and hardly any of the links (less than 1.2%). The meta-networks contain less than 5.2% of the nodes in the networks derived from texts, and less than 1.2% of

those links. Overall, the network size seems to impact the mutual resemblance of networks: the larger a network, the higher the chance that constituents from another network are also contained.

Table 97: Intersection of nodes and links per year and method

Data	Intersection of D2M and D2M+EE				Intersection of D2M and Meta-data				Intersection of D2M+EE and Meta-data			
	D2M+EE contained in D2M		D2M contained in D2M+EE		Meta-data contained in D2M		D2M contained in Meta-data		Meta-data contained in D2M+EE		D2M+EE contained in Meta-data	
	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges
2003	15.0%	5.0%	22.5%	7.7%	8.5%	0.2%	5.9%	0.2%	6.8%	1.2%	3.2%	1.1%
2004	13.5%	4.7%	20.1%	7.9%	11.3%	0.2%	8.1%	0.2%	7.1%	0.9%	3.4%	0.8%
2005	13.8%	4.8%	20.8%	8.1%	12.0%	0.2%	7.4%	0.3%	8.1%	1.1%	3.3%	1.0%
2006	13.1%	4.8%	19.6%	8.4%	13.4%	0.2%	4.5%	0.2%	8.1%	1.2%	1.8%	0.8%
2007	12.7%	4.8%	19.2%	8.3%	12.7%	0.2%	4.4%	0.2%	7.5%	1.1%	1.7%	0.9%
2008	12.7%	4.9%	19.7%	8.3%	12.2%	0.2%	4.0%	0.2%	8.0%	1.2%	1.7%	0.9%
2009	12.9%	4.8%	20.3%	8.1%	12.1%	0.2%	3.8%	0.2%	8.4%	1.2%	1.7%	0.8%
2010	12.4%	4.8%	20.2%	8.3%	10.2%	0.2%	3.2%	0.2%	8.2%	1.2%	1.6%	0.7%
Union	10.4%	4.4%	13.7%	8.9%	11.6%	0.2%	9.0%	0.3%	5.5%	0.9%	3.2%	0.6%
Ave-rage (years)	13.3%	4.8%	20.3%	8.2%	11.5%	0.17%	5.2%	0.22%	7.8%	1.1%	2.3%	0.9%
Rank nodes	2		1		3		5		4		6	
Rank links		2		1		5		6		3		4

Another important question for practical applications is whether it is worth the effort to clean auto-generated thesauri or not. The results show that using the auto-generated thesaurus as is to generate D2M+EE networks results in the retrieval of less than half the amount of nodes (48.4% for D2M, 48.5% for meta-data) and only a small fraction of the links (3.0% for D2M, 0.1% for meta-data) in comparison to network data generated with the refined, auto-generated thesaurus (Table 98). This means that with only 14.1% of the thesaurus entries left; many of which had been subject to correction (Table 90), more than twice as many nodes are found in the intersection, and also the vast majority of links is only retrieved after this cleaning process. Therefore, post-processing the output from the entity prediction models seems crucial and unavoidable.

Table 98: Impact of refinement of auto-generated thesaurus on network intersection

Data	Ratio of final D2M+EE intersection with D2M contained in intersection of D2M+EE (raw auto-generated thesaurus) and D2M		Ratio of final D2M+EE intersection with meta-data contained in intersection of D2M+EE (raw auto-generated thesaurus) and Meta-data	
	Nodes	Edges	Nodes	Edges
2003	39.4%	2.7%	63.5%	0.1%
2004	49.8%	3.1%	70.8%	0.2%
2005	46.0%	2.7%	62.7%	0.3%
2006	50.6%	3.0%	39.7%	0.1%
2007	53.7%	3.4%	48.5%	0.1%
2008	50.4%	3.0%	40.5%	0.0%
2009	48.3%	3.2%	30.8%	0.1%
2010	49.0%	3.4%	31.5%	0.1%
Union	88.1%	4.1%	115.4%	0.3%

To further compare the networks per construction method, on a very general level, one can choose between computing network metrics on the data, and identifying key entities in the data, among other network analysis methods. For this chapter, I made this choice based on the insights gained in the previous chapters: the master thesauri used in this chapter, and to a lesser degree also the auto-generated thesauri, have been subject to semi-automated as well as manual co-reference resolution. I conducted this co-reference resolution for each thesaurus separately, but reused material such as node merger list within and across the application scenarios. Based on the experimental results from chapter 2 and the practical implications of these results described in chapter 4, conducting reference resolution is essential for extracting entities from text data. However, since AutoMap does not yet offer a sufficiently accurate anaphora resolution routine, I only performed co-reference resolution on the thesauri. Consequently, the values of network metrics computed on the extracted networks can be expected to be less accurate in terms of resembling the ground truth data than key entities identified from these data. This is because key entities have been shown to be less sensitive to variations in network size and imperfect reference resolution techniques than the network metrics. Thus, key entity analysis is a more reliable strategy for analyzing and contrasting the network data than network metrics would be. Therefore, the key entity analysis method used throughout this chapter.

The results for network overlaps on the structural level had suggested that the meta-networks represent a different set of information than the text-based networks. Does this also hold true for the prominent nodes in the network? In other words, how similar are the networks per network construction method to each other on a qualitative level? I answer this question by conducting key entity analysis as follows: I partitioned the networks so that for agents and organizations, only specific instances are kept. Next, I identified the top 15 entities per network construction method (D2M, D2M+EE, meta-data), network analysis metrics (degree centrality, betweenness

centrality, eigenvector centrality, and clique count, for a definition of the metrics see Table 153), node type (agent, organization, knowledge), and calendar year (2003-2010). I output this overtime data, ranked the top entities per network type, node class, and metric, and computed the average rank per entity over the considered years. If an entity did not show up in one or more years, I assigned rank number 15 (the lowest) to it. I chose this method for identifying key players from over-time data because it jointly considers continuity and prominence of an entity, and also makes the 3D information (overtime, across methods, across entities) representable. Finally, I performed manual co-reference resolution on the key players per network type: I screened the top 15 entities for the D2M, D2M+EE and meta-data networks, and converted different spellings of entities who most likely refer to the same real-world entity to the same surface form, e.g. “bush” and “george bush” to “bush”, or “talks and meetings” and “meetings” to talks & meetings”.

The results from the key player analysis show that there is a substantial overlap in key agents, and to a lesser degree also in organizations, between D2M and D2M+EE networks (Table 99 to Table 103). For example, across the four network metrics considered on the agent level, the D2M and D2M+EE networks share 55% of the key agents. The agreements are lower on the organizations level. In the text based networks, most of the key agents are Sudanese politicians, but a few international and other African individuals are also being highly prominent, e.g. “Yoweri Museveni”, the president of neighboring Uganda. Most of the key organizations are political/ governmental units as well as armed forces, including rebel groups such as the Janjaweed and the Lord’s Resistance Army. Again, most of them are Sudanese, but the key organizations include more international entities than the key agents, mainly groups from the USA and the United Nations, such as the “International Criminal Court”, which had issued warrants for multiple Sudanese politicians, mainly because of their involvement in the Darfur conflict.

The key entity results for the D2M and D2M+EE networks also suggest that considering the content of the text bodies leads to the retrieval of highly central first names, such as “Muhammad” and “Ahmad” (these names are in gray font in Table 99). Such names cannot necessarily be mapped onto single individuals: it might be reasonable to consolidate “Joseph” and “Kony” (Joseph Kony is the leader of the Lord's Resistance Army). However, in other cases, such as “Muhammad” or “Ahmad”, which could refer to “Ahmad Al-Bashir” or “Muhammad Ahmad”; both of which are distinct, prominent figures in the Sudan, such a mapping would be more speculative, might pick up on false positives, and requires substantial subject matter expertise to make this judgment. The meta-data networks do not feature this issue, but are also

not free of entity disambiguation issues: for instance, in the meta-data, Omar al-Bashir occurs as “Omar Hassan Ahmad al-Bashir” and “Omar al-Bashir”.

The overlaps between the meta-data networks and the text-based networks are smaller than the overlaps between the text-based networks. Also, the overlap in key groups between meta-data networks and text-based networks is larger than the shared key individuals. In fact, the text-based networks and meta-data networks only agree on two key agents, namely Al-Bashir and George Bush. For organizations, the intersection is about equally split up among Sudanese and foreign or international organizations. However, most of the key organizations in the meta-networks are non-Sudanese groups, but in contrast to the text-based networks, they include groups from industry and a large portion of international NGOs. The key individuals in the meta-data networks are mainly high-profile, international politicians, such as Hillary Clinton and Ban Ki-Moon, and other prominent international figures involved in politics, such as George Clooney, who has actively promoted the development of the Sudan. Further looking into the data revealed that many of these entities are occur in the same node classes in the text-based networks, but with lower prominence.

Table 99: Key agents per network construction method and metric I*

Degree Centrality				**Betweenness Centrality**			
Key entity	D2M	D2M+EE	Meta-data	Key entity	D2M	D2M+EE	Meta-data
al-bashir	1.6	1.6	5.3	garang	1.5	1.4	
taha	1.9	2.3		al-bashir	1.9	2.9	5.3
muhammad	3.9	3.9		taha	3.4		
ahmad	5.4	9.9		bush	6.5	6.0	4.3
garang	6.4	6.1		muhammad	6.5	7.1	
ibrahim	7.6	10.6		ahmad	7.6	11.3	
hassan	8.3	9.9		ibrahim	9.0	10.5	
bush	9.1	10.9	1.8	deng	9.0	11.6	
kony	9.3	7.1		ahmed	9.9		
kiir	9.8	9.0		david	9.9		
ahmed	10.3			adam	10.0		
joseph	10.3			joseph	10.8		
ismail	11.5			michael	11.0	10.0	
abdallah	12.3			kiir	11.3		
mohamed	12.4			ismail	11.9		
ali		3.8		kony		5.0	
museveni		10.4		ali		6.0	
mustafa		10.5		james		7.8	
annan		12.0		paul		8.1	
isma		12.0		george		10.1	
				museveni		10.5	
				peter		11.8	

hillary_rodham_clinton	6.3	tony_blair	6.8
tony_blair	7.0	hillary_rodham_clinton	7.3
bill_clinton	7.3	barack_obama	7.5
michael_mcmahon	7.5	michael_mcmahon	7.6
condoleezza_rice	8.1	condoleezza_rice	8.0
ban_ki-moon	8.6	ban_ki-moon	8.4
barack_obama	8.6	osama_bin_laden	9.1
thabo_mbeki	8.9	george_clooney	9.5
tzipora_livni	8.9	mahmoud_ahmadinejad	9.9
gordon_brown	10.4	saddam_hussein	10.1
hu_jintao	10.9	gordon_brown	10.3
nicolas_sarkozy	10.9	nicolas_sarkozy	11.1
george_clooney	11.6	hosni_mubarak	12.5

* First names that may refer to multiple people grayed out in this table.

Table 100: Key agents per network construction method and metric II

Eigenvector Centrality				**Clique Count**			
Key entity	D2M	D2M+EE	Meta-data	Key entity	D2M	D2M+EE	Meta-data
al-bashir	2.5	2.0	6.3	al-bashir	1.4	1.1	5.9
taha	3.1	5.0		taha	1.6		
hassan	5.5	4.6		muhammad	4.0	3.3	
muhammad	5.6	8.0		ahmad	6.4	6.6	
ahmad	7.0	8.6		ibrahim	6.8	6.9	
kiir	7.1	7.4		garang	6.9	3.9	
garang	7.8	8.6		ahmed	6.9		
museveni	8.5			adam	8.5		
ismail	9.1			abdallah	10.0		
ibrahim	9.6			bush	10.1	8.0	1.6
kony	10.3			mohamed	10.1		
mustafa	10.4	10.6		hassan	10.9		
abdallah	10.5			ismail	10.9		
osman	11.0			mohammed	11.9		
joseph	12.0			musa	13.1		
hasan		6.4		ali		3.5	
ali		6.9		kony		7.4	
republic_field_marshal_umar		8.6		deng		9.8	
deby		9.4		museveni		10.1	
annan		10.0		james		10.9	
isma		11.3		paul		11.1	
powell		12.6		george		11.4	
				peter		13.6	
				michael		13.8	
bush			2.3	condoleezza_rice			6.5
hillary_rodham_clinton			6.9	saddam_hussein			8.5
tony_blair			7.6	nicolas_sarkozy			9.0

condoleezza_rice	8.0	tzipora_livni	9.0
bill_clinton	8.3	mahmoud_abbas	9.1
saddam_hussein	8.8	vladimir_putin	9.3
barack_obama	8.9	michael_mcmahon	9.4
ban_ki-moon	9.3	tony_blair	9.5
tzipora_livni	9.5	ban_ki-moon	11.0
osama_bin_laden	10.1	angela_merkel	11.8
michael_mcmahon	10.3	ehud_olmert	11.8
thabo_mbeki	11.0	mahmoud_ahmadinejad	12.3
robert_zoellick	11.6	barack_obama	12.9
j_scott_gration	11.8		

Table 101: Key organizations per network construction method and metric I

Degree Centrality				**Betweenness Centrality**			
Key entity	D2M	D2M +EE	Meta-data	Key entity	D2M	D2M +EE	Meta-data
government	1.0			government	1.0		
forces	2.5			forces	2.4		
spla_splm	3.5	2.6	12.8	military	3.3	5.0	
military	3.9	8.8		national_council	4.3		
us_army	6.3			spla_splm	4.9	6.4	
national_council	8.0			us_army	8.5		
lords_resistance_army	8.8	5.6	12.0	police	9.0		
janjaweed	9.8	11.9		us_congress	9.6		
united_nations	10.1	1.8	1.3	sudan_embassy	9.8		
african_union	10.3	4.6	3.6	united_nations	10.4	1.5	1.1
police	10.4			ruling_party	10.4		
sudan_embassy	10.8			dinka	11.1		
ncp	11.6	10.8		non_gov._organization	11.4		
internat._criminal_court	11.6	12.1	6.8	european_union	12.0		7.5
jem	11.6			foreign_company	12.1		
security		3.3		security		1.9	
army		6.3		southern_sudan		6.5	
humanitarian		8.5		african_union		6.8	4.1
southern_sudan		9.3		humanitarian		7.4	
party		11.0		party		7.6	
militia		11.4		army		7.8	
defense		12.3		defense		9.0	
				the_sudanese_government		11.4	
				justice		11.8	
				opposition		12.0	
				services		12.5	
				university		12.6	

united_nations_security_council	4.3	internat._criminal_court	6.3
european_union	5.5	united_nations_security_council	7.0
league_of_arab_states	8.5	al-qaeda	7.4
human_rights_watch	8.6	african_development_bank_group	10.1
united_nations_world_food_programme	9.6	united_nations_world_food_programme	10.1
liberation_movement	10.9	cninsure_inc	10.3
Intergov._authority_on_development	11.1	sudanese_tv	10.3
united_nations_children_fund	11.3	east_african_community	10.5
sudanese_tv	13.0	human_rights_watch	10.9
inter-governmental_authority	13.6	united_nations_children_fund	11.5
		china_national_petroleum_corp	11.8
		liberation_movement	13.1

Table 102: Key organizations per network construction method and metric II

Eigenvector Centrality				**Clique Count**			
Key entity	D2M	D2M +EE	Meta -data	Key entity	D2M	D2M +EE	Meta -data
government	1.0			government	1.0		
forces	2.5			military	3.0	3.9	
military	3.9	7.4		forces	3.0		
spla_splm	4.0	4.8		national_council	4.4		
us_army	6.3			spla_splm	4.5		14.1
janjaweed	7.5			sudan_embassy	7.1		
lords_resistance_army	8.5	7.8		united_nations	7.5	1.9	1.1
police	9.6			us_army	8.4		
sudan_embassy	9.6			police	9.9		
national_council	10.3			internat_criminal_court	10.9	12.3	13.4
Justice&equality_movemt	10.9			lords_resistance_army	11.1	11.5	
goss	11.0			ruling_party	11.3		
african_union	11.3	5.3	3.9	un_security_council	12.5		4.5
rebel_groups	11.5			ncp	12.6		
ncp	12.3	11.0		us_congress	12.6		
united_nations		3.5	1.5	security		1.6	
security		4.0		splm		4.4	
army		6.8		army		6.8	
humanitarian		7.0		southern_sudan		6.8	
southern_sudan		9.4		humanitarian		7.5	
the_sudanese_government		9.4		african_union		8.1	3.8
party		10.4		party		10.4	
assembly		10.8		justice		10.6	
sudan_peoples_liberation_movem.		11.0		defense		11.0	
internat._criminal_court		11.8	6.8	the_sudanese_government		11.6	

		opposition	11.8	
european_union	7.8	european_union		4.9
human_rights_watch	8.1	united_nations_world_food_programme		8.6
united_nations_world_food_programme	9.8	united_nations_childrens_fund		9.3
league_of_arab_states	10.6	cninsure_inc		10.9
united_nations_security_council	10.9	liberation_movement		11.3
cninsure_inc	11.0	human_rights_watch		13.3
liberation_movement	12.3	sudanese_tv		13.3
arab_league	12.8	talks_&_meetings		13.6
sudanese_tv	12.9	al-qaeda		13.8
united_nations_childrens_fund	13.4	security_council		15.0
inter-governmental_authority	15.0			
security_council	15.0			

In contrast to the social agent level, the text-based networks show no agreement in knowledge nodes, but a small overlap each (about two nodes) with the knowledge nodes in the meta-data networks (Table 103, Table 104). In the D2M networks, the key knowledge nodes seem to pull from a variety of topics, some of which are highly general, e.g. “political” and “emotion”. This is because almost all of the key knowledge nodes in the D2M data originated from the RER-cross classification (acronym removed from data representation in Table 103). In contrast to that, the D2M+EE and meta-networks center on negotiations between political parties and legislative issues, e.g. the Comprehensive Peace Agreement, and also economic issues (D2M+EE), e.g. “trade”. Some of the key knowledge nodes from the meta-data networks contain entities that are classified as generic agents and organizations in the text-based network data, e.g. “refugees” and “displaced persons”. The overlap between the meta-data networks and text-based networks might be larger if further, manual adjustments were made to the meta-data.

Table 103: Key knowledge nodes per network construction method and metric

Degree Centrality				**Betweenness Centrality**			
Key entity	D2M	D2M +EE	Meta-data	Key entity	D2M	D2M +EE	Meta-data
peace_process	1.0		8.6	peace_process	1.3		7.6
conflict_knowledge	2.0			time	3.3		
time	3.0			war_&_conflict	3.4		8.0
economy	5.0			literature	7.4		
security_forces	5.0			political_democratizat.	7.8		
political_democratizat.	6.1			measures_numerology	7.9		
valence_pos	6.9			valence_pos	7.9		
emotion	9.8			economy	9.0		
measures_numerology	10.4			political	9.4		

war_&_conflict	10.5		5.6	ideology	10.1		
political	11.6			war	10.1		
biomass_&_land_cover	11.8			communication	10.3		
health	12.1			sovereignty	10.5		
political_displaced	12.1			acknowledgement	10.8		
sovereignty	12.8			security_forces	11.1		
treaties_&_agreements		1.6	11.0	treaties_&_agreements		1.3	6.4
cpa		4.6		cpa		5.1	
sharing		6.1		bill		6.0	
relations		6.6		relations		6.4	
english		6.9		leading		6.5	
summit		7.5		summit		8.0	
trade		7.6		speech		8.6	
website		7.9		website		9.0	
wealth		8.1		policy		9.1	
framework		8.5		talks_&_meetings		9.4	9.1
constitution		9.8		release		9.6	
solution		10.5		constitution		10.0	
musa		10.9		peace_agreement		10.1	
education		11.0		trade		10.3	
industry		13.1		accord		11.5	
international_relations			1.6	religion			1.6
talks_&_meetings			3.9	international_relations			3.5
united_nations_institutions			5.0	refugees			4.8
rebellions_&_insurgencies			7.8	muslims_&_islam			11.0
state_departments_&_foreign_services			9.4	united_nations_institutions			11.0
displaced_persons			11.0	children			11.5
peacekeeping			11.5	armed_forces			12.1
relief_organizations			11.6	rebellions_&_insurgencies			12.4
international_law			12.5	legislative_bodies			12.5
refugees			13.6	international_assistance			13.1
paramilitary_&_militia			14.5	terrorism			14.9

5.3 Application Context II: Funding Corpus

Some federal funding agencies are obligated to publicize their information about the allocation of tax-dollars to people, organizations and ideas. For example, the National Science Foundation (NSF) provides a database with information on all previously funded research projects (NSF). The availability of such data has contributed to the transparency of state-level decision making processes. Furthermore, these data allow for addressing substantive questions such as:

- Business perspective: What team configurations (institutions, disciplines, nationality, gender, …) have been successful in acquiring funding? How does funding impact team dynamics? (Biocca & Biocca, 2002; Horta, Huisman, & Heitor, 2008)
- Social networks perspective: Which individuals and/ or organizations have been collaborating on what? What is the impact of funding research topics on the advancement of a discipline? (Folkstad & Hayne, 2011; Leung, 2007; Melkers & Wu, 2009)
- Human computer interaction perspective: Under what conditions are collaborative work teams sustaining or changing? (Cummings & Kiesler, 2005)

5.3.1 Data[17]

The Community Research and Development Information Service (CORDIS) provides a publically available database with information about the research proposals that have been accepted and funded through the "Framework Programmes for Research and Technological Development", short Framework Programmes (FPs). The FPs are funded by European Union (EU). The EU Research Council started the first FP in 1984 with the goal of stimulating and enabling competitive research in the European Research Area. The FPs have been continued since then, with the 7th FP currently under way. I used the following process to collect and normalize the Funding corpus:

For this study, I define a "project" as a CORDIS database entry for which at least a unique identification number is provided. Based on this definition, CORDIS contains 55,972 projects for FPs 1 through 6 as of December 2009. I downloaded these data into a relational database, where I performed further data management and cleaning routines. CORDIS provides the projects' start and end dates, costs and amount of funding awarded, completion status, and various key words and index terms; all of which I added into my database.

Per project, CORDIS also specifies the name, affiliation, and contact information for the project coordinator (PC). PCs are the equivalent of principal investigators in the US. The same information is given for each collaborator on a project if applicable. I define a "project with PC" as a project for which a valid entry for the project coordinator is available. An entry is considered

[17] Portions of this section and the next chapter are reprinted, with permission, from: Diesner, J., & Carley, K. 2010). A methodology for integrating network theory and topic modeling and its application to innovation diffusion. Proceedings of IEEE International Conference on Social Computing (SocComp), Workshop on Finding Synergies Between Texts and Networks, Minneapolis, MN.

as valid if it does not contain any phrase from a set of phrases[18] that I identified by manually going through the people listed in CORDIS.

The project entries also comprise three fields of unstructured, natural language text data: a title, description ("objective"), and additional information per project. The length of the text data per project varies greatly; ranging from concise summaries spanning a few sentences to elaborated descriptions. I define a "project with text" as a project for which the length of the project description plus general information exceeds a minimum length of ninety characters after disregarded certain phrases[19]. The minimum length criterion was established to discount for text fields that contain nothing but a generic header, such as "Research objectives and content:". The set of disregarded phrases are expression that I identified form the data assessed as highly common yet not content bearing in the context of this dataset (they might be parts of the proposal template).

Similar to the co-reference resolution on the Sudan thesauri, one major challenge with this dataset was the consolidation of the various instances and spellings of people's names into one consistent name per actual individuals. The findings from chapter 2 have shown that high accuracy in this step is crucial because errors during the reference resolution of names get propagated to the link and network data level, where they cause biases in network structure and analysis results. In order to identify the various references to a person, I developed a data-driven set of rules and heuristics, which I iteratively applied and evaluated for their effectiveness and correctness by manually checking their impact on the data: first, all gender and role identifiers, such as "Mrs." and "Professor" were removed from the names. Single-letter umlauts were converted into the equivalent diphthong. All tuples of identically spelled names were considered to represent the same person if their institutional affiliation and/or their address matched completely or at least in three consecutive tokens. Here, tokens are any combination of space separated letters and/or digits. The word "the" was disregarded from this process. People without a valid name entry were also disregarded. In total, my database contained 293,974 entries in the person field. Of those entries, 74.9% were valid people entries. Of those valid entries, 65.2% were identified as unique people (N = 143,700); the others are additional occurrences of the unique people.

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[18] These entries are: N/A N/A (N/A), N/A N/A, N/A, NOT AVAILABLE, NOT AVAILABLEE, Address, TBC, tbc TBC, F3 A3.

[19] The disregarded phrases are: APPROACH AND METHODS, Brief description, Objectives and content, PROJECT DESCRIPTION, Project Details, PROJECT OBJECTIVES, Research objectives and content, Summary of the project, Technical Approach

At this point, we inspected the resulting database and decided that the procedures that I had developed and implemented for the purpose of data normalization, cleaning and co-reference resolution seemed sufficient. Overall, the completeness of project entries in CORDIS varies per FPs; with later programmes being more complete. Table 104 provides an overview of the size and completeness of the CORDIS database per FP.

In this study, I consider data from FP1 to FP6 only; disregarding the downloaded information for FP7. The reason for this decision is that entries for FP7 are still being added, so that my data for FP7 would be incomplete. This is problematic as it has been previously shown that incomplete network data can lead to strongly biased analysis results (Borgatti, et al., 2006). However, any hypotheses or methodological insights gained from this study can be tested in the future with data from FP7. The same issue with incomplete network data also applies to FPs 1-3, where the ratio of projects with a person is less than 80%. For FPs 4-6, this ratio exceeds 80%, which is considered an acceptable rate for social network data.

Table 104: Size and completeness of research funding dataset

FP Number	Time frame	Number of projects	Projects with text	Projects with PC	Projects with text and PC	Number of unique people	Total number of people mentions	Average agent node weight
1	1984–1987	3,283	82.7%	77.0%	69.8%	2,404	3,246	1.4
2	1987–1991	3,884	79.9%	61.8%	56.8%	6,538	8,544	1.3
3	1991–1994	5,529	76.8%	64.8%	60.1%	14,970	18,407	1.2
4	1994–1998	15,061	79.9%	82.2%	64.1%	37,344	58,682	1.6
5	1998–2002	17,629	75.3%	95.0%	71.9%	36,420	75,355	2.1
6	2002–2006	10,586	96.8%	89.5%	86.8%	43,530	56,066	1.3

5.3.2 Network Data Construction Methods

I used the same methods for generating network data from the Funding corpus as I did for the Sudan corpus where possible. In this chapter, I work with the projects for which at least one PI as well as a text are available (projects with text and person), because both elements are of relevance for testing the network agreement in structure and key entitiesOne limitation here is that for the Funding corpus, we do not have any ground truth data from subject matter experts. However, one could argue that the social network data extracted from the list of collaborators on projects is highly accurate – even though it might be incomplete. Thus, the social network data created form the meta-data can be considered as ground truth data. The same argument could be made for knowledge meta-networks built from the predefined as well as self-defined index terms that the authors have selected for their projects.

5.3.2.1 Network Data Extraction from Texts Using the Data to Model Process

The key component of the D2M process is a thesaurus. However, since the master thesaurus built for the Sudan project cannot be expected to generalize well to the research and science domain, I built a new, domain specific thesaurus (Funding master thesaurus) for this corpus as follows:

First, I worked through the standard D2M process for creating a thesaurus and integrating it with other thesauri: I applied the same delete list as for the Sudan project to the Funding corpus. Second, I used AutoMap to compute the absolute and weighted (as per tf*idf) frequency per token, and also a list of bigrams per project. AutoMap outputs this information, but it is up to the user to select the appropriate entries. I reviewed the top 550 entries from the frequency lists and the top 1,000 entries from the bigram list (relevance of entries seemed to drop from those frequencies on), and added the concepts that I considered as relevant to the thesaurus (about 1,000). Third, I enhanced the thesaurus with meta-data from CORDIS, which is an example of a domain thesaurus (about 3,000 entries): I used the project index terms, e.g. "radioactive waste" and "fisheries", and the subprogram types, e.g. "chemistry" and "aeronautics". These terms, especially the project index terms, are partially predefined for the FPs, and need to be selected or added by the people submitting a proposal. Third, I reviewed the generic knowledge thesaurus provided in AutoMap and added the entries that seemed relevant in the context of the Funding data to the thesaurus (about 650). Fourth, I automatically deduplicated and manually cleaned all thesaurus entries, e.g. by checking for overly common terms given the domain, and splitting comma separated entries into multiple entries[20].

The resulting Funding master thesaurus contains 4,580 entries. In this thesaurus, all entries are categorized as knowledge, so that no further categorizations were necessary.

The described thesaurus construction process is a specific example for the more general case of integrating local domain thesauri (in this case derived from salient terms from text data) with standard domain thesauri (in this case FP index terms) and standard generic thesauri (in this case CASOS general knowledge thesaurus). The terminology for types of thesauri originates from the D2M process description (K.M. Carley, M. Lanham, et al., 2011). Integrating these various types of thesauri is a standard part of the D2M text coding process, and is designed to adapt previously generated thesauri to new domains and datasets. Completing this process took four work days; with most of the time costs being due to programming parsers and vetting automatically suggested entries for their appropriateness. This is a significant decrease from the amount of time needed for building the Sudan master thesaurus (six weeks), and this decrease is mainly due to

[20] The data format for thesauri in AutoMap is .csv. Since entries separated by comma (e.g. rice, rye and wheat) introduce formatting errors into the thesaurus, I put every entry after a comma into a new line.

the one-mode nature of the entries, and that less previously existing and partially conflicting thesauri had to be integrated.

5.3.2.2 Network Data Extraction from Texts Using the Data to Model Process and Entity Extractor

The same process as described for the Sudan corpus was used to suggest an auto-generated thesaurus for the Funding data (5.2.2.2). Ultimately, all entries in the Funding thesaurus need to be of type "knowledge", so that terms do not need to be classified into meta-network categories once they have been located. In this case, using the boundary detection model would be sufficient to automatically generate a thesaurus. However, since one goal here is to evaluate the quality and suitability of the prediction models in application context, I used class model 4 again (meta-network category, specificity, subtype) for creating a thesaurus.

The raw, auto-generated thesaurus had 202,304 entries with a total of 805,035 occurrences. As also observed for the auto-generated Sudan thesaurus, the additional suggestions (N lines = 27,654) did not seem highly relevant or partially redundant with entries in the regular thesaurus section. Therefore, I disregarded the additional suggestions. Next, I reviewed the predicted entries in all 44 categories. Table 105 shows these classes along with their accuracy during k-fold cross validation and their size and fit in the predicted thesaurus (last column in Table 105). The results show that two categories which performed well during K-fold cross validation (resource, money (97.7%) and agent, specific (92.3%)) did not return as accurate results in the application context. It might also be the case that these categories have few actual hits in the funding data, such that these classes suffer from sparsity. Moreover, as already observed for the Sudan thesaurus, all categories that I assessed as retrieving medium or bad results in the application context have the specificity value "specific", while "generic" entries are predicted with generally high accuracy. Table 105 also shows my decision on whether a category was kept in the thesaurus or not. Categories were excluded from further use if their accuracy seemed too low, and/or if their content seemed irrelevant in the context of knowledge networks from funding data. The quantitative impact of all refinement routines described in this section is summarized in Table 106.

Table 105: Application of prediction model to auto-generate thesaurus for Funding corpus

Class labels	**K-fold cross validation**	**Application to Funding data**			
Meta-network category, specificity, subtype	Accuracy rank	Size: Number of examples in thesaurus	Size rank	Assessment of quality	Useful for analysis?

resource, na, money	97.7%	2,792	28	medium	no
location, specific, country	97.0%	15,822	16	good	yes
org-att, specific, nationality	93.8%	20,281	12	good	yes
attribute, na, numerical	93.4%	135,573	1	good	no
time, na, na	93.4%	38,655	6	good	no
event, specific, war	92.6%	26	41	good	yes
agent, specific, na	92.3%	31,146	8	bad	no
organization, specific, gov.	90.8%	29,051	9	good	yes
org-att, specific, political	90.5%	5	44	good	yes
agent, generic, na	90.2%	98,980	3	good	yes
organization, generic, corporate	88.7%	52,534	4	good	yes
location, specific, city	88.1%	12,098	17	good	yes
organization, specific, corporate	87.2%	109,490	2	medium	yes
location, generic, country	87.1%	11,606	18	good	yes
location, specific, state-prov.	85.4%	222	36	good	yes
organization, generic, gov.	81.4%	7,058	20	good	yes
organization, specific, educational	77.8%	3,877	27	good	yes
location, generic, city	77.7%	1,641	31	good	yes
knowledge, specific, law	77.5%	4,356	26	medium	no
organization, generic, educational	72.7%	2,379	30	good	yes
location, specific, other	71.8%	16,423	15	good	yes
resource, generic, product	71.7%	4,808	24	good	yes
event, specific, na	69.0%	626	34	medium	no
location, generic, facility	67.9%	19,410	13	good	yes
organization, specific, other	67.1%	28,081	10	medium	no
attribute, na, age	66.9%	6,062	21	good	no
organization, specific, political	63.8%	31	40	good	yes
resource, na, substance	62.0%	44,124	5	good	yes
organization, generic, other	61.6%	17,982	14	good	yes
org-att, specific, religious	59.6%	10	42	good	yes
location, generic, state-prov.	52.9%	4,942	23	good	yes
resource, na, disease	50.8%	6,042	22	good	yes
knowledge, specific, language	50.0%	735	33	good	yes
location, specific, facility	49.8%	4,646	25	bad	no
knowledge, specific, art	48.5%	26,784	11	medium	no
organization, specific, religious	48.5%	174	37	medium	no
resource, na, plant	48.5%	2,684	29	good	yes
organization, generic, political	48.3%	9	43	good	yes
organization, generic, religious	47.1%	482	35	good	yes
resource, na, animal	40.4%	9,703	19	good	yes
org-att, specific, other	34.4%	96	38	medium	no
task, na, game	29.6%	3	45	good	yes
resource, specific, product	28.0%	33,508	7	bad	no
location, generic, other	18.8%	78	39	good	yes

Next, I applied the same delete list as used for the Sudan thesauri to the Funding thesaurus (hard match on complete entry). Also, I consolidated entries based on their parts of speech, subtype, specificity, and meta-network class (Table 106). As already observed for the Sudan data, entries with low frequencies are often long chains of multiple relevant entries. Therefore, I removed all entries with a frequency of one, as this seemed a suitable cut-off point.

To further assess the quality of the auto-generated thesaurus, I reviewed all entries with a frequency of 1,000 or more (N = 473). I removed a total of 7 (1.5%) of them as they seemed overly generic. At this point, the category of "organization, specific, government" still seemed to contain highly generic entries, which I cleaned out by going through all entries in that category with 1,000 instances or more. Of those unique entries, 7.5% matched in spelling when disregarding capitalization. Since in the next step, all entries were assigned to the same node class (knowledge) or the attribute class, I did not further consolidate entries based on capitalization.

Table 106: Summary of thesaurus cleaning routines and quantitative impact

Routine	Entities		Ratio of raw size	
	Unique	Total	Unique	Total
1. Raw auto-generated thesaurus	202,304	805,035	100%	100%
2. Remove categories with low performance	97,899	497,003	48.39%	61.74%
3. Apply delete list	97,375	466,895	48.13%	58.00%
4. Consolidate entries (in named order) based on parts of speech, subtype, specificity, meta-network class	91,480	466,895	45.22%	58.00%
5. Remove entries with frequency of one	17,487	466,895	8.64%	58.00%
6. Correct entries with frequency of 1,000 and more, correct and clean poorly performing categories	17,459	390,344	8.63%	48.49%

After generating one knowledge network for each projects with a text and person per FP, I unionized those networks into one graph and further inspected all nodes with a frequency of 1,000 or more (N = 725). Of those, 80 nodes (11.0%) still seemed overly common. I removed these nodes from the network data directly. I repeated this process again; concluding that the network data did not need further substantial cleaning at this point.

Overall, the process of constructing network data by using the D2M process with the auto-generated thesaurus took about two work days. The reduction of time needed to complete this process from seven days for the auto-generated Sudan thesaurus is for three reasons:

- Being able to reuse thesaurus post-processing tools that I had built for the Sudan project.

- Repeating the sequence of thesaurus refinement steps that I had identified as being practical, efficient and leading to the intended thesaurus and network data improvements during the Sudan project. However, even though it seems appropriate to reuse these steps, the best parameter setting per step can vary, and therefore needs to be tested and adjusted to the data and context.
- Generating one-mode networks as opposed to multi-mode networks, where additional time would be needed to verify the classification of entities into node classes and sub-categories, such as specificity values.

In summary, I estimate that comparable time costs of about two days would be necessary to construct and refine a new domain thesaurus with the prediction models under the following conditions:

- The same thesaurus post-processing tools and steps are employed.
- One-mode network data are constructed, regardless of the actual node type.
- The corpus is of comparable size.

5.3.2.3 Network Data Construction from Meta Data

First, for each FP with a person and a text, I created a social network by linking the project coordinator to every collaborator on a given project. Collaborators were not linked to each other in order to avoid overly dense clusters that might not reflect the reality of collaboration on research grants. I made this choice after consulting with faculty who had long-term experience in being the principal investigator on numerous grants. The chosen network formation approach leads to star structures as opposed to complete cliques per project. Stars are networks where nodes link to one central node only. Multiple instances of pairs of collaborating people are reflected in the cumulative edge weight.

Second, I created a knowledge network by linking all unique expressions from the project index terms and subprogram types per project with each other. This results in a clique or complete graph per project. The database fields considered in this step are the same that were used for the building the section of the Funding master thesaurus that uses database entries from CORDIS.

Third, I created an agent knowledge networks by linking each agent on a project (coordinators and additional collaborators) to each knowledge item per project. All outputs were generated such that they can be loaded as dynamic meta-networks into ORA.

5.3.3 Results

The results suggest that the network size in terms of nodes and edges is largely a function of the number of entities considered for network construction (Table 107): since the number of entries

in the auto-generated thesaurus (17,459) is larger than the number of entries in the Funding master thesaurus (4,580) as well as the number of entities considered for meta-data network construction (2,973), the networks produced with the auto-generated thesaurus turned out largest. While this finding is intuitive and non-surprising, it needs to be considered when constructing or using thesauri because network size has shown to correlate with network metrics (Anderson, Butts, & Carley, 1999; Faust, 2006; Friedkin, 1981; Marsden, 1990). For example, the larger the network, the lower is the density, and this density value might be independent from the social cohesion of a group, but more a result of the number of nodes and possible connections. Therefore, it seems important that people report the size of their thesauri, and also how the thesauri entries were collected: the results from the Sudan and Funding data have shown that if thesaurus entries originate from the underlying text data, such as salient terms, one can expect a higher number of hits and therefore larger networks than when adapting external thesauri to a dataset or domain.

Table 107: Network size per network construction method

FP program	D2M		D2M + EE		Meta-data			
					KK		AA	
	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges
No. of thes. entries	4,580		17,459					
1	1,127	63,832	5,099	235,606	20	23	676	575
2	1,213	90,256	5,414	295,068	91	200	5,547	5,410
3	1,401	118,584	6,079	378,072	295	1,310	14,427	14,251
4	1,623	209,968	8,648	831,452	867	6,447	35,061	34,583
5	1,655	203,350	8,694	754,356	634	9,082	34,541	48,670
6	1,680	179,298	8,146	661,564	1,299	18,888	39,848	43,033
Union	1,945	374,374	12,859	1,949,028	2,923	33,230	117,428	145,898

The results from intersecting the different types of knowledge networks suggest the following (Table 108): by far, the largest match in nodes *and* edges was observed for the D2M+EE network resembling the D2M network. More specifically, on average, 30.2% of the nodes and 31.2% of the edges contained in D2M are also represented in the D2M+EE network. Even though this effect is non-symmetric, D2M still resembles a comparatively high amount of the links contained in D2M+EE. One main explanation for the asymmetry might be the ratio of mutual resemblance is the size of the respective networks – the D2M+EE networks are about 5.1 times bigger in terms of nodes and 3.8 in terms of links than the D2M network, so that the D2M+EE has a larger pool of network constituents that can match the other network.

In contrast to the Sudan D2M networks, a larger ratio of nodes contained in the master thesaurus was found in the text data (42.5% versus 11.5%). This indicates that constructing a domain-

specific thesaurus from scratch results in a higher thesaurus coverage rate. For the D2M+EE networks, this ratio is similar for the Sudan data and the Funding data (72.4% and 73.7%); suggesting that the auto-generated thesauri are highly tailed towards and appropriate for the given domain and data set.

Similar to the results from the Sudan project, the meta-data hardly entail any of the links found in the D2M+EE networks (less than 0.7%), but some of the nodes (14.8%) from the D2M networks. An explanation for this finding could be that about 65% of the entities in the master thesaurus (used for D2M networks) were taken from the same sources (project index terms and subprogram types) as the entities considered in the meta-networks. None of these sources were used for creating the auto-generated thesaurus (used for D2M+EE networks). This rationale would also explain why the D2M networks entails almost 38% of the nodes found in the meta-data networks; the highest resemblance of nodes across all test cases.

In summary, the network size and the similarity between thesauri or look-up dictionaries used for network construction seem to be the main factors that determine the overlap of networks. Since the sources for meta-data networks and auto-generated thesaurus are disjoint pieces of information, these networks share very few constituents. In contrast to that, the master thesauri draws from the sources that are used for identifying nodes for the meta-networks and D2M networks, such that overlaps with both types of networks are more likely. However, regardless of this potential "advantage" for the D2M networks, the largest resemblance is still achieved by the D2M+EE networks with respect to the D2M networks, indicating that resemblance can also be identified from the data itself without constructing look-up dictionaries.

Table 108: Overlap between knowledge networks constructed with different methods

FP	**Intersection of D2M and D2M+EE**				**Intersection of D2M and Meta-data (KK)**				**Intersection of D2M+EE and Meta-data (KK)**			
	D2M+EE contained in D2M		D2M contained in D2M+EE		Meta-data contained in D2M		D2M contained in Meta-data		Meta-data contained in D2M+EE		D2M+EE contained in Meta-data	
	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges
1	7.7%	8.9%	35.0%	33.0%	70.0%	17.4%	1.2%	0.0%	35.0%	8.7%	0.1%	0.00%
2	7.9%	9.9%	35.4%	32.2%	45.1%	7.0%	3.4%	0.0%	22.0%	3.5%	0.4%	0.00%
3	7.3%	9.5%	31.5%	30.3%	29.2%	3.7%	6.1%	0.0%	11.2%	2.0%	0.5%	0.01%
4	5.4%	7.2%	28.7%	28.3%	40.4%	5.2%	21.6%	0.2%	11.3%	1.9%	1.1%	0.01%
5	5.5%	7.7%	28.6%	28.6%	29.7%	4.2%	11.4%	0.2%	8.4%	1.6%	0.6%	0.02%
6	5.8%	7.8%	28.0%	28.8%	20.9%	2.4%	16.1%	0.2%	4.5%	0.7%	0.7%	0.02%
Union	3.3%	4.7%	22.0%	24.5%	28.8%	4.0%	43.3%	0.4%	5.7%	1.3%	1.3%	0.02%
Average of years	6.6%	8.5%	31.2%	30.2%	37.7%	6.3%	14.7%	0.1%	15.4%	3.0%	0.6%	0.0%

Rank nodes	5	2	1	4	3	6
Rank links	2	1	3	5	4	6

In order to test whether any knowledge network resembles the social network constructed from the meta-data, I first changed the node type of the social networks to "knowledge". Otherwise, no matches could be found. The unionized and type-converted social network for all FPs (12,859 nodes, 1.95 million links) intersects with the knowledge networks as follows:

- Unionized meta-data network: no intersection.
- Unionized D2M network: intersects in 1 node and 0 links.
- Unionized D2M+EE network: intersects in 144 node and 0 links.

Further looking into the intersection of the social network with the D2M+EE network suggests that the shared nodes might be references to truly distinct entities that coincidentally overlap in spelling. Examples are "wood" and "benz" in the sense of people versus entities occurring in the context of a research project. In summary, the outcome from intersecting social networks with knowledge networks suggests that mining the content of text data is not an appropriate strategy for reconstructing social networks. Any agreement between these two types of network might be accidental, such as people's names coinciding with common nouns.

The results from the key entities analysis show that D2M and D2M+EE networks agree in a few nodes, e.g. "project", "systems", "design", and the shared nodes even rank similarly (Table 109). The meta-data knowledge networks do not overlap in key entities with the text-based knowledge networks. Even though all three types of networks contain very domain-specific terms, the most prominent entities in the D2M and D2M+EE networks are rather generic ones from the research domain, while the key entities from the meta-networks refer to more specific research areas. This difference might be explained by the data sources: the meta-data entities originate from key words, which are highly concise summaries of the content of an abstract, while the text bodies explain the projects in more detail. Taking this last point together with the low intersection rate of meta-data networks with text-based networks (at least on the link level), it seems recommendable to combine both types of networks to cover both, the common terms in a corpus as well as specific, higher-level aggregates of the content. Since the D2M+EE networks resemble about a third of the D2M network and lead to similar types of key entities as the D2M network, and the D2M networks already partially overlap with the meta-networks, it might suffice to combine just the D2M+EE networks plus the meta-data networks for this purpose.

Table 109: Key entities per network construction method (networks unionized for all FPs*

Degree Centrality				**Betweenness Centrality**			
Key entity	D2M	D2M+EE	Meta-data	Key entity	D2M	D2M+EE	Meta-data
project	1.3	1.0		project	1.3	1.0	
development	3.0			development	2.7		
european	4.0			research	3.3		
system	4.0			european	4.7		
research	4.3			europe	5.0		
develop	5.7			systems	6.0	2.0	
systems	6.3	2.7		developed	7.7		
information	8.7			develop	8.0		
data	9.3			order	9.0		
design	9.7	9.3		system	9.7		
process	11.7			application	11.3		
developed	12.0			information	11.7		
results	12.3			study	12.7	10.0	
analysis	12.7	5.3		data	13.3		
model	15.0	8.0		results	13.7		
europe		3.3		design		3.3	
study		3.7		analysis		3.7	
countries		7.7		methods		5.7	
studies		8.3		applications		7.7	
applications		8.7		tools		7.7	
field		10.0		techniques		8.0	
methods		12.3		software		10.0	
potential		12.3		field		10.3	
level		12.7		materials		11.0	
techniques		14.7		models		12.0	
				model		13.3	
				studies		14.3	
scientific_research			1.3	environmental_protection			2.7
social_aspects			3.0	policies			5.0
industrial_manufacture			5.3	social_aspects			6.3
information_processing			5.7	safety			6.7
information_systems			5.7	training			6.7
environmental_protection			6.3	renewable_sources_of_energy			7.0
training			7.0	standards			7.3
education			7.3	biotechnology			8.0
electronics			9.0	scientific_research			8.3
microelectronics			9.0	industrial_manufacture			8.7
safety			9.3	technology_transfer			8.7
renewable_sources_of_energy			10.7	information_processing			9.3
other_energy_topics			11.7	waste_management			10.7
materials_technology			12.0	information_systems			11.3
waste_management			14.0	telecommunications			13.3

* Top 15 key entities considered. Values are ranks (1 = highest) averaged over FPs 4 to 6 per metrics. Data from FP1 to 3 not considered in this table because these networks are so small that less than 15 key entities were found.

5.4 Application Context III: Enron Corpus

From its formation in 1985 until mid 2001, the Enron Corporation ("Enron") was a highly and internationally successful trader and broker for energy, commodities, and stock options. A combination of unethical to illegal business practices, such as booking losses to "special purpose entities" that did not appear on the public financial reports, and a corporate culture of making risky investment allegedly led to the abrupt fall of Enron (Fox, 2003; Fusaro & Miller, 2002; Powers, Troubh, & Winokur, 2002) (for a more detailed description of the Enron story, see also (Diesner, et al., 2005)). In December 2001, the company filed for Chapter 11 bankruptcy, which was followed by broad public outcry, and uproar among Enron's stakeholders. Both, the Federal Energy Regulation Commission (FERC) and the US Security and Exchange Commission (SEC) started investigations into Enron. A by-product of these investigations was the release of the Enron data set (described below). People have used the Enron data to answer substantive question about business networks such as:

- How is covert information disseminated in an organization, and how does the flow of covert information relate to the network structure of an organization? (Aven, 2010)
- How do the properties and structure of communication networks change during an organizational crisis? (Diesner & Carley, 2005a)
- How does the formal structure of an organizational relate to the information structure of the communication network, and how does this relationship change during a crisis? (Diesner, et al., 2005)

5.4.1 Data[21]

The Enron email dataset was originally released online by the FERC in May 2002. FERC made the data available in order to allow the public to understand why they had started investigations into Enron. It is crucial to stress the fact that this dataset contains data from many individuals who were not involved in any of the actions that were subject of the Enron investigation.

Each email contains three sources for network data:

- Explicit relational data provided in the email headers, i.e. the email addresses of the senders and receiver(s).

[21] The description of the Enron dataset is based (Diesner, et al., 2005).

- Text bodies, which may contain explicit and implicit descriptions of relationships between socio-technical entities.
- Additional meta-data, such as time stamps and folder names.

FERC collected a total of 619,449 emails from 158 Enron employees, mainly from senior managers. The original version of the dataset had a variety of integrity problems. Next, Leslie Kaelbing from MIT purchased the data. The data was then acquired by researchers from SRI, notably Melinda Gervasio, who fixed many of the integrity problems and released their version of the dataset online. In March 2004, William Cohen from CMU put the data online for research purposes. Cohen's version of the dataset contains 517,431 distinct emails from 151 unique users. These emails are organized in 150 user folders with a little less than 4,700 subfolders. Some messages were deleted in response to requests from affected employees. Invalid email addresses for which a recipient was specified were converted to addresses of the form "user@enron.com", and to "no_address@enron.com" where no recipient was specified. Further consistency checks done by Andres Corrada-Emmanuel from the University of Massachusetts via applying check-sums (MD5) to email bodies revealed that the corpus actually contained 250,484 unique emails from 149 people.

We started off building the CASOS Enron database by using the version provided by Jitesh Shetty and Jafar Adibi from ISI. The ISI researchers had refined and normalized the dataset by dropping blank, duplicated and junk emails, and emails that had been returned by the system due to transmission errors. The resulting corpus consists of 252,759 emails organized in 3,000 user defined folders from distinct 151 people. The ISI group put the Enron data in a MySQL database which contains four tables; one for *employees*, *messages*, *recipients* and *reference information*. We chose this version of the dataset for our work because the normalization processes that were done to it seemed appropriate to us and were well documented, and the data structure met our needs. I refer to this version of the Enron email dataset as the CASOS Enron dataset.

This dataset also involved a co-reference resolution challenge: the entities or nodes represent email addresses, not people. This is troublesome for cases in which people use more than one email address, such that unique individuals would occur as multiple nodes in the network. We have corrected for this issue mapping e-mail addresses to individuals based on information about Enron employees as provided in publically available data sources. These external data sources contain information about the location of the Enron branches that people worked in, as well as their job titles. For a full description of the preparation of the CASOS Enron dataset see (Diesner, et al., 2005). In summary, we were able to map 1,234 email addresses to 557 distinct individuals for who we also know their actual name. In these refined data, the number of email addresses per person ranges from 1 to 17, the average number of emails per person is 2.2, and the

standard deviation for this number is 1.9. The number of emails for which both, a sender and at least one receiver, can be mapped to a unique and disambiguated individual is 52,866 (21.1% of the number of unique emails identified by Corrada-Emmanuel). We equally consider entries in the *to*, *cc*, and *bcc* fields as receivers. This version of the CASOS Enron dataset is used herein for analysis.

For the previous two application scenarios, the time slicing of the corpora was done based on calendar years (Sudan corpus) and funding periods (Funding corpus). The first approach could also be used for Enron. However, since the Enron data offer a rare glimpse into a real-world, organizational crisis, I decided to construct time slices around critical periods in Enron's history, even though no empirical questions about the Enron crisis are addressed herein: the Enron crisis started to emerge in August 2001, when Jeffrey Skilling suddenly resigned as CEO, and Kenneth Lay took over this position again. In the same month, Sherron Watkins, one of Enron's vice presidents, wrote a whistle-blower letter to Lay. The crisis then took off in October 2001, when Enron began to publically report its humongous losses. The stock market reacted with a sharp drop in the price for Enron shares; which ultimately led to the company's insolvency. Based on this timeline, I created three time periods that are used in this study:

- May to June 2001: 6,091 emails. This period can be considered as a control case. During this period, Enron's fall was not yet in sight.
- August – September 2001: 3,711 emails. The period in which the Enron crisis emerged.
- October – December 2001: 11,042 emails. The period of Enron's downfall.

Taken together, the emails in these three time periods account for 41.0% of all emails in the CASOS Enron dataset.

5.4.2 Network Data Construction Methods

The same methods for network data construction as used for the Sudan and Funding corpus were also used for the Enron corpus where possible.

5.4.2.1 Network Data Extraction from Texts Using the Data to Model Process

I started to create the Enron master thesaurus by reusing multiple local domain thesauri that we had previously built for the CASOS Enron data by using the D2M process. For that D2M process, we had employed an earlier entity extractor that I had also built by using conditional random fields-based machine learning techniques and integrated into AutoMap (Diesner & Carley, 2008a). After combining the various local domain thesauri, I added standard domain thesauri for Enron which contain the names of people. These thesauri were generated from the explicit meta-data in the email headers on senders and receivers of emails. Finally, I enhanced

the Enron master thesaurus with entries from the standard generic thesauri that are provided in AutoMap: I reviewed the entries in the standard agent, organization, event, task, knowledge, location, role (generic agents) and time thesaurus one by one, and added the entries that I considered as relevant to the master thesaurus. In fact, some entries from the local domain thesauri for Enron had also been made available in the standard generic thesauri, such that these thesauri had some overlaps, which I removed.

After generating and inspecting D2M network data, I identified a few more nodes that appeared as key players, but for which the overlap in case-insensitive spelling with other, more common terms had contributed to the high frequency and prominent network position of threes nodes. An example is “price”, which is the last name of a former Enron employee, but the term is more often used in the context of the price of shares. I removed these nodes from the master thesaurus, and regenerated the network data. The final Enron master thesaurus contained 6,963 entries.

Completing the construction of the Enron master thesaurus took two work days. As already observed for the Funding master thesaurus, reusing and adapting existing thesauri significantly cuts the time costs for thesaurus construction.

5.4.2.2 *Network Data Extraction from Texts Using the Data to Model Process and Entity Extractor*

Class model 4 was used again to produce the auto-generated Enron thesaurus. The raw thesaurus contained 144,204 entries with a total of 633,597 instances. Like in the previous applications scenarios, I disregarded the additional suggestions (N=9,228) for the same reasons as outlined before. Again, I reviewed each category. Table 110 shows the outcome of this process, and also specifies which categories were not further considered due to low performance.

Table 110: Application of prediction model to auto-generate thesaurus for Enron corpus

Class labels	**K-fold cross validation**	**Application to Funding data**			
Meta-network category, specificity, subtype	Accuracy rank	Size: Number of examples in thesaurus	Size rank	Assessment of quality	Used for analysis?
resource, na, money	97.7%	19,228	9	good	yes
location, specific, country	97.0%	2,528	21	good	yes
org-att, specific, nationality	93.8%	920	26	good	yes
attribute, na, numerical	93.4%	98,886	2	good	yes
time, na, na	93.4%	76,008	3	good	yes
event, specific, war	92.6%	17	42	good	yes
agent, specific, na	92.3%	60,220	4	medium	yes*
organization, specific, gov.	90.8%	518	29	good	yes
org-att, specific, political	90.5%	98	39	good	yes

agent, generic, na	90.2%	38,565	6	good	yes
organization, generic, corporate	88.7%	23,098	8	good	yes
location, specific, city	88.1%	11,966	11	good	yes
organization, specific, corporate	87.2%	2,167	22	good	yes
location, generic, country	87.1%	1,083	25	medium	no**
location, specific, state-prov.	85.4%	1,422	24	good	yes
organization, generic, gov.	81.4%	4,214	18	good	yes
organization, specific, educational	77.8%	10,705	12	good	yes
location, generic, city	77.7%	479	31	good	yes
knowledge, specific, law	77.5%	8,964	14	good	yes
organization, generic, educational	72.7%	545	27	good	yes
location, specific, other	71.8%	5,395	16	good	yes
resource, generic, product	71.7%	437	34	good	yes
event, specific, na	69.0%	486	30	bad	no
location, generic, facility	67.9%	4,077	19	good	yes
organization, specific, other	67.1%	9,979	13	medium	no**
attribute, na, age	66.9%	4,793	17	good	yes
organization, specific, political	63.8%	450	33	good	yes
resource, na, substance	62.0%	1,479	23	good	yes
organization, generic, other	61.6%	6,043	15	good	yes
org-att, specific, religious	59.6%	10	44	good	yes
location, generic, state-prov.	52.9%	3,835	20	good	yes
resource, na, disease	50.8%	531	28	bad	no
knowledge, specific, language	50.0%	61	41	good	yes
location, specific, facility	49.8%	16,956	10	medium	yes*
knowledge, specific, art	48.5%	25,871	7	bad	no
organization, specific, religious	48.5%	155	35	bad	no**
resource, na, plant	48.5%	100	38	good	yes
organization, generic, political	48.3%	148	36	good	yes
organization, generic, religious	47.1%	146,747	1	bad	no**
resource, na, animal	40.4%	470	32	medium	no**
org-att, specific, other	34.4%	16	43	good	yes
task, na, game	29.6%	82	40	good	yes
resource, specific, product	28.0%	43,734	5	bad	no
location, generic, other	18.8%	111	37	good	yes

* entries with frequency of 50 and more reviewed and corrected if needed, all entries maintained

** entries with frequency of 50 and more reviewed and corrected if needed, all other entries deleted

Next, I refined the auto-generated thesaurus as summarized in Table 111. Then, I used the refined thesaurus to extract meta-networks from the email bodies by employing the D2M process. I further refined the thesaurus by reviewing all nodes in the networks with a frequency of at least 100 (N=1,167). Based on this review, I deleted overly common entries from the thesaurus, and modified category assignments where needed. Regenerating and inspecting the nodes suggested that the thesaurus and network data are sufficiently clean now, particularly for

high frequency nodes. Overall, post-processing the auto-generated Enron thesaurus took about two work days, which is comparable to the time costs for building a master thesaurus from existing sources.

Table 111: Summary of thesaurus cleaning routines and quantitative impact

Routine	Entities		Ratio of raw size	
	Unique	Total	Unique	Total
1. Raw auto-generated thesaurus	144,204	633,597	100%	100%
2. Remove categories with low performance	66,330	386,737	46.0%	61.0%
3. Apply delete list	66,068	360,896	45.8%	57.0%
4. Consolidate entries (in named order) based on parts of speech, subtype, specificity, meta-network class, spelling regardless of capitalization	60,373	360,896	41.9%	57.0%
5. Remove entries with frequency less than five	8,549	275,952	5.9%	43.6%
6. Correct entries with frequency of 100 and more	8,546	275,497	5.9%	43.5%
7. Correct entries after reviewing nodes with frequency of 100 and more in unionized graph (N = 1,167), re-deduplicate nodes	8,255	272,647	5.7%	43.0%

Table 112 shows the frequency distribution of nodes classes in the final auto-generated thesaurus. As also observed for the Sudan data, overall, generic social agents (individuals and groups) occur more often in the text data than specific agents. This finding further supports the importance of considering unnamed entities for socio-technical network analysis in addition to the traditional focus on specific entities.

Table 112: Frequency distribution of entities classes in thesaurus*

Class	Ratio in full thesaurus, unique	Ratio in full thesaurus, total	Average number of repetitions per unique entity
agent, specific	<u>26.9%</u>	<u>10.9%</u>	13.4
attribute	<u>24.6%</u>	<u>28.2%</u>	37.9
time	<u>16.8%</u>	<u>19.7%</u>	38.7
resource	7.5%	3.7%	16.3
agent, generic	7.0%	<u>12.8%</u>	60.7
location, specific	6.7%	6.2%	31.0
organization, specific	3.5%	4.1%	38.5
knowledge, specific	2.8%	1.1%	12.5
organization, generic	2.7%	<u>11.4%</u>	137.1
location, generic	0.8%	1.6%	66.2
knowledge	0.4%	0.1%	10.6
resource, generic	0.2%	0.2%	22.3
task	0.1%	0.0%	14.8

Total	100.0%	100.0%	33.0

* values over 10% underlined

Reviewing the auto-generated Enron thesaurus and respective networks at different stages of refining the thesaurus, I made the following observations:

First, I had hypothesized that since the Enron data are from a different time period, domain, and writing style than the data used for training the prediction models, the prediction accuracy would be lowest for this application scenario. The results do not support this hypothesis: based on my qualitative reviews presented in this chapter, the prediction accuracy was about the same across all three corpora, with the same classes being problematic throughout.

Second, the errors made by the prediction models are similar across all three applications:

- A most commonly observed type of error was the assignment of terms that typically occur in lower case to classes of specific agents or specific organizations for cases in which these terms occurred capitalized. This happens if the impacted terms appear at the beginning of a sentence, or when all letters are in upper cases, such as for acronyms (Sudan, Funding) and "yelling" in emails (Enron).
- Erroneous cases with a low class assignment frequency (less than ten, especially one up to five) often involve chains of multiple entities (Sudan, Funding) or of relevant entities in conjunction with highly frequent, domain specific terms, such as "subject" and "Forward" (Enron).
- Specific entities are predicted with a lower accuracy than a) generic entities and b) entities to which the specificity distinction does not apply.
- Categories performing low during formal model testing are more likely to also perform low when applying the models to new and unseen data; with two exceptions to this rule:
    - Categories that performed very well during formal model assessment might return poor results during application, especially for specific agents.
    - Categories that performed low during formal model assessment might return good results during application.

5.4.2.3 Network Data Construction from Meta Data

Similar to the procedure used for the Funding data, I built the meta-networks from the information explicitly given in the email headers: I used the information about senders and receivers to generate directed social network. This information was also used as standard domain thesauri for the Enron master-thesaurus (used for D2M networks). The weight of a link is the number of emails exchanged between the involved agents. Any type of receiver (to, cc, bcc) is

equally considered as an email recipient. Even though these social networks might be incomplete since not all of Enron's emails are present in the dataset, they can be considered as a type of ground truth data.

5.4.3 Results

Table 113: Network size per network construction method

Data	D2M		D2M+EE		Meta-data		Number of emails
	Nodes	Edges	Nodes	Edges	Nodes	Edges	
No. of thes. entries	6,963		8,255				
Pre-crisis	1,504	27,618	3,506	54,846	448	3,092	6,901
Emergence of crisis	1,547	21,071	3,149	43,452	433	2,295	3,711
Crisis	1,665	31,624	3,989	71,068	435	4,721	11,042
Union graph	1,940	55,956	4,794	132,064	513	7,365	21,653

The auto-generated thesaurus contains 1.2 more entries than the master thesaurus, but leads to the retrieval of 2.3 more nodes and 2.1 more edges (Table 113). Also, 58.1% of the entities in the auto-generated show up in the D2M+EE networks, while 27.9% of the entries from the master thesaurus appear in the D2M networks. This indicates again that the auto-generated thesaurus is more effective.

A crucial finding here is that the text-based networks contain 2.1 (D2M+EE) and 2.3 (D2M) more nodes than more edges than the meta-data networks. This effect is not necessarily evident from the density values of the networks (Table 114), which are almost identical for the meta-data networks and the D2M networks. Nonetheless, this finding indicates that the windowing technique for link formations applied to network data generates more dense networks than the social networks from the email headers, which can be considered as ground truth data.

Table 114: Network density per network construction method

Data	D2M	D2M+EE	Meta-data
Pre-crisis	0.02	0.01	0.02
Emergence of crisis	0.01	0.01	0.01
Crisis	0.02	0.01	0.03
Union graph	0.02	0.01	0.02

In order to analyze the structural overlap of the meta-data networks with the text-based networks, I extracted the connections between specific agents only as they resemble the same type of nodes as the entities considered in the meta-data. Applying this constraint, the intersection between the meta-data networks (proxy for ground truth) and the text-based networks is particularly high on the node level for the D2M networks resembling the meta-data networks (86.8%), and

moderately high for the vice versa case (54.9%) (Table 115). This result is intuitive because all of the entities contained in the meta-data network were also added as entries to the master thesaurus, and most of the specific agents in the master thesaurus originate from that set of entities. Since the list of email senders and receivers was not added to the auto-generated thesaurus, the mutual resemblance of the meta-data networks and the D2M networks is minimal.

Table 115: Overlap between social networks (agents, specific only) constructed with different methods

Data	Intersection of D2M and Meta-data				Intersection of D2M+EE and Meta-data			
	D2M contained in Meta-data		Meta-data contained in D2M		D2M+EE contained in Meta-data		Meta-data contained in D2M+EE	
	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges
Pre-crisis	60.1%	9.6%	88.4%	19.6%	6.7%	0.06%	2.4%	0.02%
Emergence of crisis	53.6%	7.0%	83.6%	14.4%	6.0%	0.09%	2.3%	0.02%
Crisis	51.1%	10.6%	88.5%	17.5%	6.7%	0.06%	1.9%	0.02%
Union graph	57.7%	12.0%	94.0%	22.7%	6.8%	0.15%	1.9%	0.04%
Average of years	54.9%	9.1%	86.8%	17.2%	6.5%	0.1%	2.2%	0.0%

Comparing the text-based networks of specific agents shows that even though no shared entries were explicitly added to both thesauri, both networks still pick up on a small amount of common agents (left-hand side section in Table 116). In order to test for the overall structural agreement between the text-based networks, I also considered all node classes for comparison, including but not confined to specific agents (right-hand side section in Table 116). This comparison shows that D2M+EE resembles D2M more than vice versa to almost the same amount as D2M+EE networks are larger in nodes as well as edges than the D2M networks. This finding further confirms the prior observation that structural overlap correlates with network size.

Table 116: Overlap between networks constructed with different methods

Data	Intersection of D2M and D2M+EE Agent, specific network				Intersection of D2M and D2M+EE Entire meta network			
	D2M contained in Meta-data		Meta-data contained in D2M		D2M contained in D2M+EE		D2M+EE contained in D2M	
	Nodes	Edges	Nodes	Edges	Nodes	Edges	Nodes	Edges
Pre-crisis	10.2%	1.5%	5.3%	0.7%	18.9%	4.4%	8.1%	2.2%
Emergence of crisis	9.6%	1.1%	5.7%	0.5%	18.4%	3.8%	9.0%	1.8%
Crisis	9.6%	1.7%	4.6%	0.8%	18.5%	4.0%	7.7%	1.8%
Union graph	9.0%	1.6%	4.0%	0.7%	16.8%	4.3%	6.8%	1.8%

For this application scenario, key player analysis was conducted on the level of specific agents, since this is the only type of nodes that is available in all three types of networks. The meta-data networks and D2M networks share almost the same list of thesaurus entries or entities considered for network construction, and most of the key players in D2M originate from this list (77.5% on average, those with first and last name). However, the key players between the meta-data networks and the D2M networks hardly overlap, and except for eigenvector centrality, show no greater agreement than the D2M+EE network with the other two types of networks (Table 118).

Taking the findings from the structural agreement and overlap in key players together, it seems that even though some types of networks have significant intersections in their form or on a quantitative level, they lead to suggestion about who the main agents in a network would be.

In the Sudan study it had been shown that both types of text-based networks are highly likely to identify single first names as specific agents. While these nodes are correctly assigned, they often cannot be associated with specific individuals who have a first *and* last name. This issue is even more likely to occur in the Enron data, since in the US-American setting, people often address and refer to others by their first name, and also sign emails with their first name. The results shown in Table 118 confirm this assumption for the D2M+EE networks, and to a lesser degree also for the D2M networks. In fact, most occurrences of specific agents with a first *and* last name are likely to originate from email headers that occur in email bodies due to the forwarding of emails, and to a lesser degree also from email signatures, which are not very common among the internal emails in Enron. Therefore, the results suggest that with the master thesaurus (D2M), it is more likely to retrieve names from meta-data within the text bodies (signature of forwarded emails), while with the auto-generated thesaurus (D2M+EE), instances of first names only, which are more likely to occur in the actual content of an emails, are more often identified as key agents. As described for the Sudan thesaurus, mapping these agents to a first *and* last name might be infeasible because multiple people might have the first name.

Table 117: Key agents per network construction method I

Degree Centrality				**Betweenness Centrality**			
Key Entity	D2M	D2M+EE	Meta	Key Entity	D2M	D2M+EE	Meta
lloyd_will	2.0			lloyd_will	1.0		6.3
rebecca_mark	2.3			rebecca_mark	2.0		
jeff	2.7	1.3		jeff	4.0	1.7	
jeff_dasovich	3.7		2.3	dorland_chris	4.0		
thomas_paul_d	5.0			susan_scott	6.3		
kean_steven_j	6.0			dave	6.7		
steven_kean	7.7			eric	6.7		
paul_kaufman	8.0			mathew_frank	7.7		
susan_scott	8.7			kean_steven_j	8.3		

dorland_chris	9.0			thomas_paul_d	8.3		
james		2.7		john		3.7	
john		3.3		jim		5.0	
richard		4.3		mike		5.0	
dasovich		5.0		richard		5.0	
steffes		5.0		james		6.3	
steve		8.0		kim		6.3	
susan		8.0		steve		6.7	
mike		8.7		jones		7.0	
shapiro		8.7		chris		8.3	
susan_mara			4.3	louise_kitchen			2.7
james_steffes			4.7	john_lavorato			3.0
louise_kitchen			5.0	timothy_belden			4.7
mike_grigsby			5.7	kevin_presto			5.0
mary_cook			6.0	mark_haedicke			5.3
richard_shapiro			6.3	tom_may			6.7
liz_taylor			6.7	christi_nicolay			7.0
iris_mack			7.0	kay_mann			7.0
john_lavorato			7.0	mark_taylor			7.3

Table 118: Key agents per network construction method II

Eigenvector Centrality				**Clique Count**			
Key Entity	D2M	D2M+EE	Meta	Key Entity	D2M	D2M+EE	Meta
jeff_dasovich	1.3		1.7	rebecca_mark	1.3		
jeff	1.7	3.0		lloyd_will	1.7		6.7
thomas_paul_d	3.3			jeff	3.0	3.3	
paul_kaufman	4.3		6.0	susan_scott	5.0		
lloyd_will	4.7			thomas_paul_d	5.3		
richard_shapiro	7.0		3.7	dorland_chris	5.7		
jeff_richter	7.0			elizabeth	8.0		
rebecca_mark	7.7			kean_steven_j	8.0		
alan_comnes	8.7			mathew_frank	8.3		
alan	9.3			dave	8.7		
james		3.0		john		1.0	
dasovich		4.0		james		3.0	
steffes		4.0		robert		4.3	
richard		4.7		steve		4.7	
shapiro		5.0		richard		5.0	
mara		6.0		mike		6.7	
susan		6.3		tom		8.7	
linda		9.3		jim		9.0	
john		9.7		chris		9.3	
susan_mara			3.3	louise_kitchen			3.3
james_steffes			4.0	john_lavorato			4.0
mary_cook			6.3	kevin_presto			4.3
steven_kean			6.3	timothy_belden			4.3

marie_heard	7.3	christi_nicolay	6.0
harry_kingerski	8.0	mark_haedicke	6.0
mark_palmer	8.3	steven_kean	6.3
		don_baughman	7.0
		liz_taylor	7.0

5.5 Conclusions

The application scenarios presented in this chapter are representative for situations where there is a need for distilling information about relevant entities and their relations from text corpora, and where the definition of what is "relevant" varies depending on the research question and context. What is generally needed in such situations is the transformation of text data into concise, accurate and reliable reductions and abstractions of the original material, in this case network data. The results from this chapter suggest the following answers to my research questions:

1. *How do the prediction models perform in real-world application scenarios?*

The assessments of the auto-generated thesauri and the network data constructed lead to the following conclusions:

1. For the majority of the entity classes supported by these models (N = 44 at most), instances are predicted with an accuracy that is high enough for being employable in practical applications to new datasets and domains.
2. In contrast to my initial hypothesis, no meaningful differences in prediction accuracy were observed for different publication times, genres and writing styles of the considered text data.
3. The auto-generated thesauri generalize better to new datasets and domains than the master thesauri, which are built in a more manual fashion.
4. Creating and refining auto-generated thesauri is more efficient (in terms of time costs) and effective (in terms of entity coverage rate) than creating and refining master thesauri.
5. As observed in chapter 3 for formal prediction model assessment, the prediction accuracy of classes seems to be independent of the number of instances per class.
6. The auto-generated thesauri also feature limitations with respect to prediction accuracy. Therefore, it seems recommendable to verify and if needed correct the auto-generated thesauri. In this chapter, heuristics, methods, and tools were developed to help with this process.
7. Classes that perform low during formal model assessment are more likely to show low performance in the application as well. However, class with high accuracy during formal

model assessment can return poor results in the application, and vice versa. The implications of this finding is that is seems recommendable to:

- Verify the performance of each class prior in the application context.
- If the verification of each class is not feasible, e.g. because it is too time consuming, disregard the classes that perform poorly across all three application scenarios (named below).

8. Several classes show poor performance across all application scenarios. Since these scenarios involved data from different times, domains and writing styles, the poor performance of these classes might generalize to other datasets:
   - agent, specific
   - organization, specific, corporate
   - event, specific
   - location, specific, facility
   - knowledge, specific, art
   - resource, specific, product
9. Specific entities are predicted with a lower accuracy than a) generic entities and b) entities without a specificity value. This might be due to data sparsity, i.e. a lower number of specific than generic agents contained in the text data. This assumption is supported by the findings from this chapter.
10. Prediction accuracy drops with cumulative frequency of the predicted entity, i.e. the number of times that an entity is observed in a particular class and – if applicable – further sub-categories, such as specificity and subtype.
11. Two main types of errors were observed for the auto-generated thesauri across all three application scenarios:
    - Terms that typically occur in lower case get assigned to the wrong category (mainly specific agents and organizations) if they occur in capitalized form. This might be due to data sparsity, and mainly happens if these terms occur at the beginning of a sentence, or when all letters of a term are capitalized, e.g. for acronyms and "yelling" in emails. These cases can be removed from the thesauri by comparing the spelling and part of speech of any two entities, outputting the cases that differ in capitalization only, and making a decision about them by either manually vetting them, or relying on the frequency counts, which are included in the auto-generated thesauri.
    - Terms with a low frequency (less than ten, especially one to five) often involve chains of multiple entities or of relevant entities in conjunction with highly frequent, domain specific terms. These can be removed from the thesauri by

disregarding suggestions with low frequencies. Again, this decision should be based on screening the thesaurus and identifying a suitable cut-off value.

12. Entries in the agent generic and organization generic classes tend to overlap for the case of references to groups, such as "students" or "workers". In the CASOS standard thesauri, such entries also occur in either thesaurus category. For practical applications, it seems justifiable and efficient to merge these two classes.

2. How do the network data and network analysis results obtained by conducting relation extraction which uses the entity extractor developed chapter 3 compare to alternative methods for constructing network data from the same corpora?

The comparison of the network data generated with different methods on the structural level and with respect to key entities lead to the following conclusions:

1. Ground truth data constructed by subject matter experts are hardly resembled by any automated methods that analyze text bodies, and even less so by exploiting existing meta-data from text corpora. This means that trying to reconstruct social network data from the content of text body will lead to largely incomplete networks.
2. Networks extracted from text bodies by using auto-generated thesauri (D2M+EE networks) resemble networks generated with master thesauri (D2M networks) more strongly in terms of nodes and edges than vice versa.
3. D2M+EE networks resemble meta-data networks more closely than D2M networks. This is because in this study, master thesauri were enhanced with information from the same sources that were used for defining the nodes in meta-networks. At the same time, auto-generated thesauri and meta-data networks are built from disjoint pieces of information, namely text bodies and meta-data on the texts.
4. Agreements in structure and key entities are mainly impacted by two factors:
    - Network size: the larger a network, the higher is the chance that it resembles parts of network data constructed with other methods. This finding is relevant as it has been shown that network metrics can correlate with network size (Anderson, et al., 1999; Faust, 2006; Friedkin, 1981; Marsden, 1990). Consequently, observed differences in these metrics across networks constructed with different methods might be independent of differences in the underlying network, but rather be a consequence of the network construction methods; and in the case of this study especially the link formation methods.

- Overlap in thesaurus content: similarity in the entities considered in the thesauri or for network construction strongly impacts the agreement in structure and key players.

5. Structural agreements are always considerably higher on the node level than on the edge level. However, this finding is heavily impacted by the link formation methods used in this chapter, for which the limitations had been measured and summarized in chapter 2.
6. Meta-data networks are less likely than text-based networks to suffer from co-reference resolution issues. This is mainly because somebody or some algorithm has already solved this issue. In contrast to the meta-data networks, both types of text based networks (D2M+EE, D2M) tend to retrieve single first names as key entities, which can be difficult to map to unique people with a first and last name.
7. For social networks (agents and organizations) constructed from news wire data, meta-data networks are more suited for providing an overview on major international key entities and their relations, while the text-based networks are more appropriate for gaining a localized view on geo-political entities, and also for retrieving information about their culture.
8. Meta-data networks retrieve more specific entities (in a qualitative, not quantitative sense) than the text-based networks. For the case of knowledge networks, meta-data networks return more informative key entities than the text-based networks, while text-based networks identify many common place terms as key entities.
9. Overall, it seems recommendable to combine meta-data networks with text-based networks to cover both, the common or highly salient terms in a domain with more specific, domain dependent information. For this purpose, it might suffice to combine the networks built with auto-generated thesauri (D2M+EE) with the meta-data networks plus any information from subject matter experts if available for the following reasons:
    - The D2M+EE networks resemble the D2M networks better than vice versa.
    - The D2M+EE networks lead to similar types of key entities than the D2M networks.
    - The D2M networks already partially overlap with the meta-networks.

5.6 Limitations and Future Work

The knowledge gained from this chapter is limited by the data sets that I had collected, prepared and used herein, and the methodological choices I made. I discuss both point below, and suggest solutions for practical applications with the given methods and technologies as well as ways to improve these methods and technologies in future work.

5.6.1 Data Level

Even though the Sudan corpus was collected through LexisNexis from a variety of sources, most of the texts are from newspapers and news magazines that appear in English. The biases that are contained in these sources are carried over to the extracted network data. Especially the analysis of meta-data had shown that one of these biases is a focus on high-profile politicians from the Western world. Also, the largest Sudanese newspaper considered is the Sudan Tribune, which is published in France.

The CORDIS database might be incomplete, i.e. some funded project might be missing. There is no way for us to validate the completeness of the provided information. Also, the database is incomplete for the listed projects. Moreover, the CORDIS database does not list rejected proposals, and no public source might provide this information. Also, the co-reference procedures that I applied to the individuals in the data leave further room for improvement: errors such as typos could be further eliminated by employing edit-distance algorithms. Also, detecting variations in names due to name changes, e.g. when women adopt their husband's last name, would require further careful checking of institutional affiliations and addresses.

The Enron data are also likely to be incomplete as only the email archives from 158 people were collected, and people might not have stored all of their emails in these archives. Similar to the limitations pointed out for the cleaning of the Funding data, the data cleaning process might be incomplete: people with identically spelled names and email addressed might have been aggregated, people for who we could not map a real name to one or more email addresses were disregarded from analysis, and people included in the analysis might have used additional email addresses that we were not able to associate with them. However, the advantage with the CASOS Enron email dataset is that nodes represent individual people as opposed to email addresses. This might entail the risk of conflating various "personas" or roles that people occupy when using different email addresses, such as one for professional matters and one for private affairs.

5.6.2 Methods Level

Various methodological limitations also apply to the conclusions drawn from this chapter:

1. Automated text coding: Even though automated text coding (D2M process) speeds up computer-assisted text coding, it involves various weaknesses: entity extraction tools are more likely than humans to retrieve duplicates and near duplicates (Bond, et al., 2003). This was also observed in the application contexts. On the other hand, machine coding offers perfect intercoder-reliability (at least for non-probabilistic methods) and excludes accuracy losses due to

fatigue and coding biases due to individual contextualization or interpretation of the data (P. Schrodt, 2001).

2. Impact of human decisions and need for subject matter expertise: Even though many of the text coding and network analysis routines used in this chapter are largely supported by software tools, there are still numerous manual and computer-assisted steps involved. These steps are not only time consuming, but also require human decision making processes. It was shown that these processes imply the risk of errors and reliability issues (chapter 2) and biased, and require substantial subject matter expertise. In this chapter, a single person (me) made these decisions, and tried to acquire the subject matter expertise as needed. This might be representative for real-world text coding projects. However, the following strategies were used to mitigate the mentioned risks: all decisions were made in close coordination with my advisor, according to the norms and rules established in CASOS, and based on the knowledge about the impact of text coding choices on network data from chapter 2. Also, I have over six years of experience in using the text coding methods applied in this chapter. In future work, the validity of my findings should be further scrutinized by additional people who validate the auto-generated thesauri, master thesauri, and resulting network data.

3. Co-reference resolution: The main task for which these decisions and subject matter expertise were needed was co-reference resolution, which had to be performed in order to validate and refine the master thesauri and auto-generated thesauri, to refine the network data, and to clean the datasets. Since co-reference resolution on texts, thesauri and network data is not yet supported by routines in AutoMap or ORA, I did perform these tasks by hand, which has limitations beyond the aforementioned time costs and risk of incompleteness, errors and biases. For example, I merged some nodes for which it was not perfectly clear if all instances of these nodes map to the same real-world person (e.g "salva" to "kiir"). For these cases, I considered the entity frequencies (first name appears with similar or lower frequency than last name) and alternatives (merging only if no other agent with same first name or last name occurs in the union of the annual networks) to the best of my knowledge and limited subject matter expertise. For instance, in the Sudan data, some of the most frequent agent nodes were single names, e.g. "ibrahim" (5,822 instances) and "muhammad" (6,202 instamces). These could not be mapped with high certainty to more specific agents. In conclusion, the addition of co-reference resolution routines that operate on the network data level and the text level (for thesaurus generation) level would be a highly useful extension to this work. Such routines would need to be able to reason about the similarity of nodes not only based on string similarity, which would fail for cases like "Salva" and "Kiir", but also by exploiting external domain knowledge as well as structural features of the network data. Alternatively, conducting reference resolution on the input text data

prior to generating thesauri would solve this issue in the same way as it is solved for meta-data networks, such that reference resolution is not pushed off to the thesaurus or network data level.

4. Link types: All approaches for extracting network data from texts used in this chapter treat links as untyped network constituents. Another valuable extension to this work would be the classification of links. In prior research, various scales for categorizing links between agents or organizations as conflicting, cooperative or neutral have been developed and evaluated (Goldstein, 1992; McClelland, 1971). In political science, the categorization of links is a state of the art process in event data coding (Bond, et al., 2003; P. A. Schrodt, et al., 2008). Machine-learned based methods for learning prediction models for link types have also been provided (RC Bunescu & Mooney, 2007; D. Roth & Yih, 2002).

5. Link formation: The findings are limited by the link formation approach, namely windowing, used for the extraction of relational data from text data. The results in chapter 2 had shown that windowing involves the risk of false positive links. To further test the conclusions drawn from this chapter, the same tests could be repeated with alternative link formation methods.

6. Prediction models for thesaurus generation: The qualitative accuracy assessment of the thesauri that were auto-generated with the entity extractor built in chapter 3 had shown some limitations that occurred in all three applications scenarios. Based on the synthesis of these limitations as presented in the prior conclusions section, I suggest exploring whether retraining the models with the following modifications leads to more accurate thesauri in application scenarios:

- Train without the parts of speech feature.
- Train with a lower iteration rate, e.g. 300, and test performance in the application scenarios.
- Add the classes that consistently perform low in the application scenarios to the “none” class.
- Provide more examples in the look up dictionary for the classes that consistently perform low in the application scenarios (Ciaramita & Altun, 2005; Cohen & Sarawagi, 2004).
- Use different, domain-specific look up dictionaries to train models for particular domains.

Yet another approach to achieve higher accuracy of the auto-generated thesauri without revising the thesauri for every new project would be to use more profound domain adaptation techniques (Daumé, 2007; Gupta & Sarawagi, 2009; Satpal & Sarawagi, 2007). These techniques do not necessarily require the retraining of the prediction models, which is a time-costly process, but use statistical techniques to adjust a trained model to a new domain.

7. Incompatibility between methods and tools: The insights are limited by a given, technical constraint: the tools used herein for the D2M process and conducting network analysis convert all thesaurus entries to lower case, and perform node comparison on a lower case basis. On one hand, this work flow is consistent and coherent. It also is efficient, because it eliminates the need to add terms that typically occur in lower case, but occasionally appear capitalized, to the thesaurus in both forms. On the other hand, adjusting the thesauri so that they contain only lower case entries caused the loss of information, such as the disability to differentiate capitonyms. An example are terms like Rice, Straw and Bush (people) and Turkey (organization) versus rice, straw, bush and turkey (generic natural resources); all of which would have been relevant for analyzing socio-cultural networks such as the Sudan data, but were typically reduced to the meaning with the higher frequency count. Another example was the resulting incidental overlap of key entities from the networks constructed from the meta-data (wood as resource) and text bodies (wood as person) for the Funding corpus: for these data, I hypothesize that differentiating between terms in upper case and lower case form will show that author networks reconstructed from texts authored by these people are even smaller than those identified in this study. In future work, two strategies could be employed to mitigate this limitation: first, one could adjust the tools or use different tools in order to conduct analysis on a case-sensitive level. This strategy was beyond the scope of this thesis, but once implemented, the analyses conducted herein could be repeated in order to identify the qualitative and quantitative impacts of this change, and the robustness of the network data (extraction methods) towards these changes. Second, the parts of speech, which are also output with high reliability by the prediction models and in the auto-generated thesauri, could be used to disambiguate thesaurus entries and their matches in the text data. This would be particularly beneficial for distinguishing between proper nouns and common nouns (the examples shown above), and for eliminating a common type of error that the prediction models cause in the auto-generated thesauri: there, common nouns could be disregarded if the occur in upper case form, which happens at the beginning of sentence and possibly due to the sparseness of this situation, often cause misclassifications as specific agents or locations. This second strategy might be less effective than the first one, but is also less invasive in terms of changing existing technologies.

6 Methodology for Jointly Using Text Data and Network Data: Advancing the Enhancement of Social Network Data with Content Nodes

6.1 Introduction and Problem Statement

When text data pertaining to networks are available as a source of information, people have several options for how to use the content of text data for network analysis. I have consolidated these choices into five methodological approaches, which are discussed below. This discussion concludes with the selection of one approach, for which I develop and test a resolution to the main limitation with this approach. In the context of this chapter, I distinguish between the content or substance of text data (actual text bodies), which have been written by people, versus meta-data, which can also contain text fields, e.g. index terms and key words, and can originate from human authors or algorithms.

6.1.1 Disregarding Text Data for Network Analysis

Even though text data are often acquired as a natural by-product of (network) data collection processes, this does not mean that they are necessarily useful or relevant for further analysis. Thus, if the content of text data does not contribute to the understanding of a network, the text data can be disregarded all together. Examples are the Funding and Enron datasets described in the previous chapter (5.3.1), for which explicit social network data (who collaborates or communicates with whom) were acquired along with the corresponding text data (abstracts of research proposal and email bodies). However, for conducting classic social network analysis, these text data might be irrelevant. Another argument in favor this strategy is a statement by White (1963, p. 5), who said that the “distinctive aspect of roles in formal organization must be not their content but their articulation, the structure they form.” Furthermore, disregarding text data for network analysis is the most efficient approach discussed in this chapter.

The main limitation with this approach is that to the best of our knowledge, there are no empirical studies that provide information on the conditions under which the consideration of text data for network analysis is useful or not, and how much of a difference in understanding a network it would make. Even though many methods and technologies are available for extracting network data form text data[22], what is missing here are decision support mechanism that help to assess whether considering text data for a network analysis project will offer additional value or

[22] For a review of these methods see section 3.2, more elaborated reviews are offered in (J. Diesner & K. Carley, 2010; Mihalcea & Radev, 2011).

not. Even though this problem is not addressed in this chapter, the previous chapter has shed some light on this; showing that:

- Networks constructed from meta-data do hardly resemble ground truth data, while networks extracted from texts can partially lead to this effect.
- The mutual resemblance of networks extracted from text data and meta-data networks is low in terms of nodes and minimal in edges, but networks extracted from text data still resemble meta-data networks better than vice versa.
- Networks extracted from text data tend to be larger in terms of the number of nodes, edges, and node and edge classes than meta-data networks and network data constructed in collaboration with subject matter experts, which impacts the value of certain network metrics.
- For social networks, key entities from text-based networks allow for a more localized or domain specific view on networks than meta-data networks do. For knowledge networks, the inverse effect was observed: meta-data networks comprise more informative and descriptive key nodes, while the key nodes from text-based networks provide a more generic view.

6.1.2 Represent Content as Links

The content of textual information can be abstracted or reduced to the existence, weight or likelihood of nodes and links. In the simplest and widely used version of this approach, any observed occurrence of the exchange of information between a pair of entities is be converted into a link, and the (weighted or scaled) frequency of these occurrence is used as the link weight (see for example Cataldo & Herbsleb, 2008; Diesner, et al., 2005; Doerfel & Barnett, 1999; PA Gloor & Zhao, 2006; Haythornthwaite, 2001; C. Roth & Cointet, 2010). The main critique with this approach is that it may fail to considered relevant information about a network (Alderson, 2008). Scholars in communication science, among others, have previously emphasized this limitation: Corman et al. (2002, p. 164) argue that we “cannot reduce communication to message transmission”. Danowski (1993, p. 198) states that “travelling through the network are fleets of social objects”, and capturing them requires the analysis of the text data.

A different instance of this approach, which is not subject to the abovementioned limitation, is the construction of directed influence diagrams about uncertain events. In these diagrams, subject matter experts denote events, the causal relationships between the events, and link weights that indicates the (estimated) likelihood of an event causing an effect (Howard, 1989; Pearl, 1988). This process is the basis for constructing probabilistic graphical models. A particular family of

these models, namely conditional models, was used for representing dependencies between text tokens and node labels in section 3.3.

6.1.3 Analyze Text Data and Network Data Separately

The content of text data can be considered, but analyzed separately from the network data. This strategy is typically used to acquire additional information about nodes that have been identified as key entities with respect to certain network metrics. An example for this approach is link analysis, previously referred to as the production of Anacapa diagrams, where network data are generated as part of criminal investigations: once a network diagram has been constructed from evidence, hypotheses for further investigations are developed (Harper & Harris, 1975; Howlett, 1980). One method for testing these hypotheses is to go through the records and protocols collected on individuals. Another example is text analysis based on grounded theory methodology: there, human coders identify relevant concepts (codes), document the codes in memos, aggregate similar codes into variables, and arrange the variables into relational structures (H. Bernard & Ryan, 1998; Lewins & Silver, 2007). These relational structures represent the implicit relations in the data, and support the development of models and theories (Glaser & Strauss, 1967). All text passages that have been associated with a code or variable can then be retrieved, and in-depth, qualitative text analyses can be conducted on them.

While this approach is suited for gaining thorough understanding of some phenomena, the main limitation is that it does not scale up (Corman, et al., 2002).

6.1.4 Relation Extraction

When the structure and behavior of networks are encoded in the text data itself, network data can be extracted from the texts. This approach was discussed in detail in the prior chapters, but needs to be mentioned here for completeness. Relation Extraction offers an alternative solution when reducing or abstracting the substance of text data to nodes and links causes a loss of relevant information, and when the entire text basis needs be considered for analysis in an efficient fashion. Once relational data have been extracted from texts, they can be used as stand-alone network data for further analysis, or being jointly analyzed with existing network data. For example, in the last chapter, I had concluded that fusing meta-data networks with text-based networks allows for combining different views on a network (section 0).

6.1.5 Jointly Using Text Data and Network Data

There is a large body of literature from various disciplines that supports the argument that jointly utilizing text data and network data can lead to a more comprehensive understanding of networks (and texts) than exploiting either data source alone or in a disjoint fashion (Alderson, 2008;

Bourdieu, 1991; K.M. Carley & Palmquist, 1991; A McCallum, Wang, & Mohanty, 2007; J. Milroy & Milroy, 1985; Mohr, 1998; C. Roth, 2006). The problem here is that methods and respective tools for putting this goal into action are less well established (Dabbish, et al., 2011; C. Roth & Cointet, 2010). I am focusing my discussion of this approach on the most widely used instance of it:

6.1.5.1 Network Enhancement with Content Nodes

The simplest yet powerful approach to integrating text data and network data is to enhance a network with nodes that represent the content of text data. I refer to these nodes as "content nodes", and to this approach as "network enhancement with content nodes". Content nodes typically represent salient terms from the text data. These terms can be found, for instance, by computing (weighted) term frequencies per (lemmatized) term, and picking the terms with the highest scores (C. Roth & Cointet, 2010). The content nodes are then linked to the agents who have generated, processed or disseminated the respective information. The resulting data can readily serve as input to regular network analysis methods (see for example K. M. Carley, et al., 2007; PA Gloor & Zhao, 2006; Makrehchi & Kamel, 2005).

An example for network enhancement with content nodes is SmallBlue, an expert finder system that makes inferences based on the social network data about IBM's employees (Ehrlich, et al., 2007). A study of SmallBlue has shown that enhancing purely social network data with information derived from people's blog entries, emails, chats, bookmarks, and other social media sources improves the systems' performance in terms finding experts (Ehrlich, et al., 2007). This was particularly true when searching for experts on very specific, narrowly defined problems. I have used an even simpler version of network enhancement with content nodes in the previous chapter, where I connected the social network of collaborators on research grants to nodes representing index terms for these projects. These index terms are not from the actual text bodies, but are rather very general proxies for the content of the text data that were selected by the authors. In summary, network enhancement with content nodes is an efficient engineering solution that is easy to implement, and is widely and successfully used for practical purposes.

From a scientific point of view, the main critique of this approach centers on the arbitrariness of the content node identification process: first, the respective network enhancement process does not consider theories or prior knowledge about the relationship between the social positions and roles of individuals or groups in a network, and their language use (Corman, et al., 2002; Woods, 1975). Consequently, connecting any one actor to content nodes happens independently from connecting other actors to content, even though it has been shown that social relations impact the content that people produce, perceive and obtain, and vice versa (this relationship is discussed

din more detail in the next background section). Second, the mutual influence of content networks or semantic networks and social networks is considered at most in one direction, i.e. the impact of social networks on concept networks, but not vice versa (Cowan, Jonard, & Zimmermann, 2002; Harrer, Malzahn, Zeini, & Hoppe, 2007; C. Roth & Cointet, 2010). This is problematic as there is prior research in support of the argument that without considering the content of text data, we are limited in our ability to understand the effects of language use in socio-technical networks, including the transformative role that language can play on networks, and the interplay and co-evolution of information and the structure and behavior of networks (Bourdieu, 1991; J. A. Danowski, 1993; Giuffre, 2001; J. Milroy & Milroy, 1985; Mohr, 1998).

In summary of the above discussion of methods for considering text data and network data, I conclude that a) Relation Extraction and b) jointly using text data and network data are best suited for considering the substance of text data if needed. Relation Extraction has been addressed in the previous chapters. For this chapter, we decided to focus on advancing the method of enhancing networks with content nodes by addressing the outlined limitations. In the following background section, I discuss theories and prior work relevant for finding a resolution to the arbitrariness of adding content nodes to social networks. The main purpose with this chapter is to identify, implement and test a methodological advancement to this method. The resulting procedure is demonstrated in two application scenarios.

6.2 Background: Theories and Models for Jointly Using Text Data and Network Data

This section provides the background on possible theoretical underpinnings for enhancing networks with content nodes. More specifically, the concepts of social positions, social roles and groups are reviewed. The background section concludes with the selection of a network-centric approach for jointly considering text data and network data. In the methods section, an interdisciplinary, computational procedure is developed for putting this approach into action. In the operationalization and results section, this procedure is applied to two datasets; showing how the methodology needs adjustment to be practically useful.

6.2.1 Relationship between Social Positions, Social Roles and Groups in Networks and Language Use

6.2.1.1 What are social positions, social roles and groups?

In network analysis, the concept of social position is defined as a collection of nodes that are similar in their activities, interactions and ties with respect to other positions (Breiger, Boorman, & Arabie, 1975; R. S. Burt, 1976; Wasserman & Faust, 1994). Thus, positions are equivalence

classes. Conducting positional analysis basically means to identify, represent and analyze nodes partitioned into subsets. In each partition, the nodes are linked in similar ways to the nodes in other positions (Lorrain & White, 1971). This process is commonly referred to as grouping, with blockmodeling being a prominent example for grouping (White, Boorman, & Breiger, 1976). The outcome of positional analysis is a mapping of nodes to groups.

From a network analytical point of view, the concept of social roles is defined as patterns of relations between nodes or positions (Merton, 1968; Nadel, 1957; White, 1963). The focus with roles is on associations among relations that link social positions, not relationships between nodes. Furthermore, roles are not defined over pairs of positions, but on the network level, where roles describe how each pair of positions is related to each other. Individual nodes can have multiple roles. Furthermore, primitives of roles, e.g. the kinship relationships of descendants, can be combined into chains of roles or more complex roles, such as the descendant of a descendant (grandchild) (White, 1963). The outcome of role analysis is a joint representation of identified positions (one node per position) and the relations between them. Common representations of this output are image matrix, where the nodes are positions and the cell values denote the presence or absence of a connection, and reduced graphs, which are visualizations of image matrices (Wasserman & Faust, 1994).

Despite these formal, network-centric definitions of social positions and roles, theories about them are often formulated in terms of the properties of (groups of) individuals (Merton, 1968). These properties can be structural ones (Lorrain & White, 1971; Winship, 1988) or other behavioral signatures:

One example for structurally defined roles are the classic power roles from network analysis, which are defined in terms on node level-centrality metrics as introduced in section 1.2.1 (Mandel, 1983). These power roles include brokers or gatekeepers (high in betweenness centrality), lobbyists (high in eigenvector centrality) and celebrities (high indegree centrality), among others. More recent examples for structurally defined roles are roles that express the exclusiveness with which nodes from certain node classes have access to nodes from other classes, such as the exclusive access of some agents to resources and knowledge (K.M. Carley, 2002b).

An instance of roles defined over behavioral signatures homophily, which assumes that people who are similar in their personal characteristics tend to form links with each other, such that networks feature homogenous sets of people (McPherson, Smith-Lovin, & Cook., 2001). Further, research in anthropology has shown that the presence of people who play certain informal social roles in groups, e.g. expressive leaders (people who organize social events, social

directors) correlates with a cohesive group structures. At the same time, the absence of other informal roles, especially of instrumental leaders (people important for getting things done) is associated with fragmented groups (Johnson, et al., 2003). Such empirically grounded insights about the relationship between roles and network structure are essential as the cohesion or fragmentation of a group is related to its performance (D. Krackhardt, 1994), and the potential for conflict in groups and their wider environment (Humphreys, 2005). Another example for a behavioral property that has been used to formulate hypotheses and theories about social roles is language use (Humphreys, 2005; Marcoccia, 2004; J. Milroy & Milroy, 1985). This point is elaborated in detail in the next section (6.2.1.3).

Two closely related areas where fundamental theories about network positions and roles were developed are the diffusion of innovation, and opinion leadership (Coleman, et al., 1966; Rogers, 1962; B. Ryan & Gross, 1943): these roles, which mainly comprise innovators, early adopters, different types of majority, and laggards, and also the concept of boundary spanners, have been adopted and further advanced across disciplines (R. S. Burt, 1999; E. Katz & Lazarsfeld, 2006; M. Katz & Shapiro, 1986; Mc Allister & Studlar, 1991; K. H. Roberts & O'Reilly III, 1979; Tushman, 1977), and also been tested for their current applicability (Duncan J. Watts, 2007). Currently, role analysis is also a heavily researched topic in social media analysis: for example, roles that individuals occupy in discussion forum and learning systems have been identified by analyzing the structural position of individuals in a graph (Stuetzer, Carley, Koehler, & Thiem; Welser, Gleave, Fisher, & Smith, 2007) as well as the text data provided by network participants (Golder, 2003; Haythornthwaite & Gruzd, 2008).

In general, the underlying assumption with all network-oriented research on social positions and roles is that the identified patterns in observed relations are indicative of the roles that nodes in different positions play. The number of theories about the relationship between node properties and positions and roles is humongous, which is mainly due to the following reason: “since there are numerous ways to formalize the idea of types of ties, there are numerous ways to formalize the ideas of network role and network position” (Wasserman & Faust, 1994, p. 464).

In summary, due to the less strict definition of roles in theories about networks and human behavior, roles are not only specified and therefore operationalizable on the (global) network level, where the definition of roles is typically rather abstract (Wasserman & Faust, 1994; White, et al., 1976), but also on the local level, i.e. on the level of nodes and positions (Mandel, 1983; J. Milroy & Milroy, 1985; Sailer, 1979; Winship, 1988). This review has furthermore shown that theories about social positions and roles often originate from the consideration of structural as well as other behavioral characteristics of (groups of) nodes; with one of these features being language use.

6.2.1.2 General concept of groups

Social positions and roles are a particular instance of groups that can be identified from networks. Zooming out from the specific level of positions and roles to a more general level, groups represent sets of nodes that are structurally similar to each other (Wasserman & Faust, 1994). A commonly used alternative to the notion of structural equivalence, i.e. roles and positions, is the idea of groups defined by cohesion. Simple forms of cohesive groups that have been previously introduced in this thesis are triads, cliques and components (Table 153, (D. Krackhardt, 1998; Wasserman & Faust, 1994)). More elaborated notions of cohesion involve partitioning a graph based on network properties of nodes and links, such as betweenness centrality (Girvan & Newman, 2002). The main difference between groups defined by structural equivalence versus by cohesion is that in the first category, group members might be dispersed over disjoint or distant parts of the network, which is not the case for group members from the second category.

6.2.1.3 How do social positions, roles and groups relate to language use?

What do we gain from considering texts *and* networks over using only either one data source? Research on language change has shown how the network position or group membership of social agents is indicative of the social roles that people or groups play with respect to language change (Gumperz, 1982; Lippi-Green, 1989; J. Milroy & Milroy, 1985; L. Milroy, 1987). The Milroys have found that boundary spanners who adopt new facets of their vernacular are most effective in spreading these changes into the wider community. More specifically, the structural properties of people who are effective in introducing and diffusing innovation are a plethora of weak ties (for the notion of strong and weak ties see Granovetter, 1973), marginality to any adopting group, and an attitude of not considering the elements of change as a significant network marker. In contrast to that, people who are located at the core of cliques and hubs can afford and in fact tend to resists to impacts that deviate from the group's norms, and that originate from outside their network group. This area of research has concluded that people's attitude towards language change impacts greater sociolinguistic patterns of the adoption and diffusion of vernacular. For some of this work (J. Milroy & Milroy, 1985; L. Milroy, 1987), multiple types of ties have been considered, namely kinship, friendship, collaboration, and being neighbors, which illustrates the point that the analysis of roles and positions is more informative if multiplex data are used (Wasserman & Faust, 1994; White, et al., 1976).

Work by Eckert (1998) has shown how in groups that are formed for a certain purpose (communities of practice), linguistic styles are continuously developed and shared by the group members. Consequently, the homogeneity of language use in such groups increases over time.

This work ties back to the concept of homophily (McPherson, et al., 2001). Related to this concept, Fitzmaurice (2000) used historic data (letters) to investigate how strategies alliances between individuals impact their language use. She showed that in the contexts of hostile or competitive situations, people who may have opposing agendas but a shared goal, form dense network clusters. In these groups, language use becomes more homogenous. There is also support for the reversal of this effect: We have shown how during an organizational crisis, the entropy of the content of interpersonal communication decreases, while polarization increases (Diesner, Carley, & Katzmair, 2007).

Guiffre (2001) revealed a positive relationship between the stylistic perceptions of artists as expressed in reviews written by art critics, and the decisions made by gallery owners about concurrently exhibiting work by different artists. The more favorable the reviews for any two artist, they more likely it becomes that they get co-exhibited. This relationship is self-reinforcing over time; ultimately leading to more or less successful careers in art.

Roth and Coinet (2010) found that the relationships between social capital, measured as degree centrality of authors, and semantic capital, operationalized as highly central documents, differs depending on the type of collaboration that a group in involved in: for scientists who co-publish together, social capital and semantic capital show a significant, positive covariance. For contributors to social media (bloggers), a different trend was observed: poor semantic capital does not translate into low social capital, i.e. authoring non-popular or marginal comments does not hurt the social status of a person.

In summary, prior work from different areas has provided empiric evidence as well as a few theories and models about the relationship between language use and the membership of people in groups in networks. Also, this review has shown that jointly utilizing texts and networks requires interdisciplinary work at the intersection of natural language processing, network analysis, and maybe other fields, especially sociology and anthropology. While this intersection still forms a small yet growing area of research, no commonly accepted methodology for putting this idea into action has yet emerged. In the next section, I build upon prior work in natural NLP and artificial intelligence to develop such a methodology that integrates prior knowledge about groups with an efficient, non-arbitrary method for identifying content nodes that also are grouped into sets of similar entities.

6.2.2 Roles, Positions and Groups at the Text Data Level

The idea of positions, roles and groups has also been conceptualized for the text level. I focus my review of prior work on this topic on research related to network analysis. Partitioning words into groups of similar or equivalent sets has a long tradition in network analysis:

Initially, researchers have mainly used multi-dimensional scaling (MDS) as a method to this end (Woelfel, Holmes, Cody, & Fink, 1988). MDS basically transforms a squared matrix into Euclidean distances between nodes (Kruskal, 1977). The output of this process is a two-dimensional, graphical representation of the proximity between any pair of nodes. The assumption with or interpretation of this semantic space is that the closer two nodes are, the stronger is their contextual semantic association. Especially in communication science, MDS has been used to cluster words from documents (Doerfel & Barnett, 1999; Woelfel, et al., 1988), and also to partition communication networks into groups of participants who are similar in their communication behavior (W. D. Richards, 1971; W. D. Richards & Rice, 1981). Another methods that can be used for partitioning words is Latent Semantic Analysis (LSA); also referred to as Latent Semantic Indexing (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990). LSA is based on the same matrix operations and underlying assumptions as MDS, and has also been used for practical applications of grouping words (Smith & Humphreys, 2006). In LSA, Principal Component Analysis (PCA) is applied to word-document co-occurrence matrices, and the output is also a two-dimensional representation of word or node proximities.

There are three main disadvantages with the spatial models described above (Griffiths, et al., 2007): first, the revealed relations are always symmetric, even if they are truly asymmetric. For example, a stalker is closer to his victim than vice versa. Second, these models do not allow for term disambiguation, because all semantic associations of heteronyms appear in equal proximity to the focal concept. Consequently, unrelated terms would be placed into the same position. Third, these models can wrongfully suggest coherent local substructures (groups) such as triads or cliques. For example, politicians might be friends with trade union leaders and business executives, which does not imply that the trade union leaders are also friends with the business executives.

An alternative model that also takes document-word co-occurrence matrices as an input and outputs terms grouped into positions is topic modeling; a technique based on Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003). In contrasts to MDS and LSA, LDA is based on the assumption of a probabilistic, generative process according to which some assumed latent, unobservable structure generates words, which can be observed. One can perform Bayesian inference on the observed words to infer the latent structure. The specifics of the assumed latent structure and the causal (generative) dependencies between the considered variables can be expressed as probabilistic, graphical models. Typically, topic models are represented via plate notation.

The commonality between MDS, LSA and LDA is that these techniques are unsupervised machine learning technique that basically reduce the dimensionality of text data to unlabeled sets

of terms that are related through their context-specific, semantic associations (Griffiths, et al., 2007). In topic modeling, these sets are called topics. In contrast to MDS and LSA, LDA can disambiguate between different meanings of a word (the same term can appear in multiple topics), and does not enforce symmetric relationships or triads and closures of larger node groups. In topic modeling, each topic comprised a set of words where the weight per word indicates the strength or likelihood of the association of a word with the topic. The assignment of words to topics is a non-exhaustive and non-exclusive process, meaning that not all texts terms are descriptive for topics, while certain terms or phrases may occur in multiple topics. Topic modeling has become a state of the art technique for grouping words in sets that express the gist of some body of texts. To a lesser degree, topic modeling has also been used in the context of network analysis (J. Diesner & K. M. Carley, 2010a; A McCallum, Wang, & Mohanty, 2007).

Another approach to grouping words is based on the theory or assumption of spreading activation. This approach assumes that mentioning a concept triggers the activation of semantically related concepts, which can be retrieved from human or electronic memory (Collins & Loftus, 1975; Collins & Quillian, 1969). Translating this idea into network analysis terminology means that a concept is defined by its ego-network. An ego-network comprises all nodes in the one-step environment of a node, such that the size of the ego-network equals the node degree (K.M. Carley, 1997a, 1997b; Mohr, 1998). Since spreading activation uses a similar data structure or representation for nodes and edges like MDS and LDA do, this approach also suffers from the inability to disambiguate identically spelled terms with different meanings.

Finally, Carley and Kaufer (1993) have proposed a typology for grouping concept nodes in semantic networks into eight ideal types that describe the communicative connectivity and communicative power of nodes. Nodes are assigned to these types based on their combined score on three dimensions: density (total node degree), conductivity (betweenness centrality), and consensus (frequency of ego-network of a node). For example, words scoring high on conductivity, but low on consensus and density are categorized as “buzzwords”. Only extreme values on these dimensions (“high”, “low”) are considered, such that the grouping process is not necessarily exhaustive. This approach has a limitation that generalizes to automated methods for grouping words based on their value for network metrics in general (J. Diesner & K. M. Carley, 2010a): the magnitude or range of these values have no absolute, predefined or theoretically rounded interpretations, such as a density of 0.2 would be high, low or medium. Instead, most of these metrics can only be interpreted in comparison to the values computed on other networks or the same network at another point of time. Therefore, appropriate cut-off points for determining when a node scores high or low on a metric can only be defined as rule sets or heuristics. This requires a data-driven, case-wise decision-making process, and also a basic understanding of

network metrics. The resulting limitation is that this approach to grouping nodes cannot be fully automated, and moreover does not generalize from one dataset to another without testing the appropriateness of cur-off values and potential adjustments (J. Diesner & K. M. Carley, 2010a). Consequently, this process is expensive in terms of time and human resources.

6.2.3 Summary of Insights Gained from Review of Theories, Models and Methods for Jointly Utilizing Text Data and Network Data

Summarizing the insights from the review section leads to the following conclusions:

1. The approach of enhancing network data with content nodes is practicable and efficient. However, the identification of content nodes is arbitrary and lacks a theoretical foundation. Also, the mutual influence of network data and language use cannot be appropriately considered.
2. This limitation can be alleviated by drawing from the rich body of previously developed theories, models and methods for grouping nodes (social actors, other socio-technical entities, and words) into structurally similar network partitions. Two notions of groups were discussed:
    - Groups defined in terms of equivalence classes (social positions), and relations between those positions (social roles). In contrast to the initial strict definition of roles and positions and due to theoretical and methodological advances, analysis of roles and positions can be conducted not only on the network level, but also on the level of nodes and node groups.
    - Groups defined by cohesion.
3. Topic modeling has been identified as an efficient and appropriate technique for grouping words.
4. Prior research has shown that jointly considering groups of nodes and text data for network analysis has lead to insights that could not have been gained by using either data source alone.

6.3 Methodology

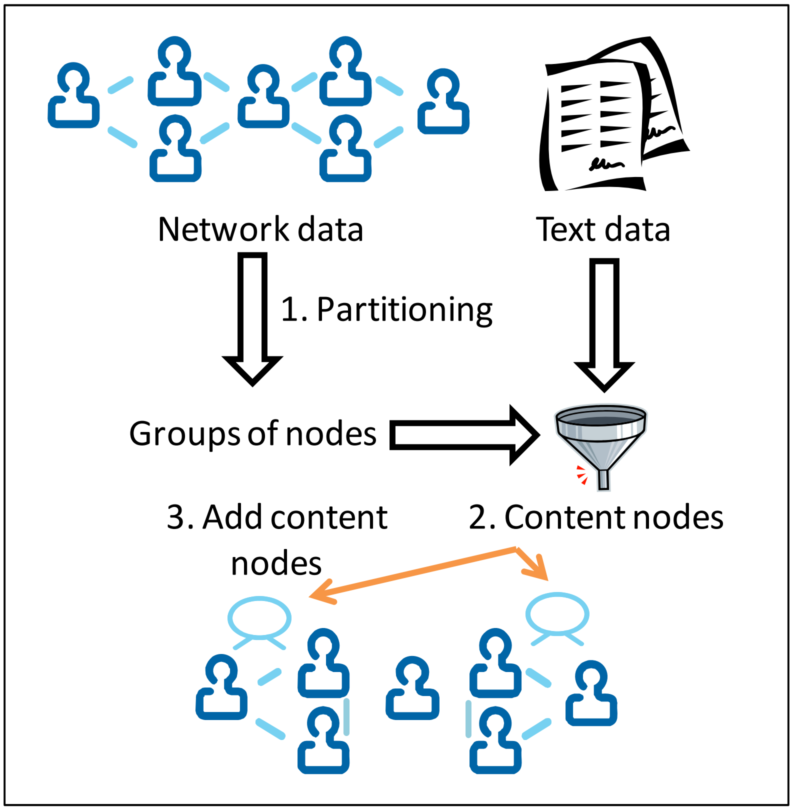
In this section, I turn the conclusions made above into the proposition of a three step methodology that is meant to improve the method of enhancing networks with knowledge nodes such as that the selecting of agents to link to knowledge as well as the identification of knowledge nodes are non-arbitrary. Figure 12 illustrates the intended workflow.

Steps one and two require decisions or strategies for operationalizing the grouping of actor nodes and the selection of content nodes. Step three is a straightforward or deterministic matrix

operation. Therefore, I focus the following section and subsequent analysis on steps one and two, and provide a user guide for step three.

1. Partition social networks into groups.
2. Identify content nodes per group. This step serves the identification of shared content per group. One option is topic modeling on the texts originating from the nodes per group.
3. Enhance social network with content nodes.

Figure 13: Workflow for proposed methodology



6.3.1 Partition Networks into Groups

The first question is: What social positions, roles or groups to consider? Wassermann and Faust (1994) recommend to use rather general and abstract conceptualizations of the structural location of nodes in networks when formalizing social positions and roles, and also to use flexible descriptions of patterns or types of relations between nodes. The outcome from prior research supports the appropriateness of this recommendation: we had identified and compared the content produced by who occupy roles that represent their disposition and ability to motivate or inhibit language change in social networks (J. Diesner & K. M. Carley, 2010a). These roles were based on work empirical work and a resulting theory by Milroy and Milroy (1985; 1987). Being

in the position to change or maintain norms in a group and possibly also in the wider society bears opportunities and risks for members of either group. In order to assign nodes to these two groups, we had developed role templates that combined multiple node-level network metrics that we evaluated as being are relevant for detecting the considered role. Then, we identified nodes that fit either template by computing the selected metrics on all members, and screening the results to define boundary or cut-off values for scoring high, medium and low on each metric. Finally, we performed topic modeling on all texts per group. In the context of this chapter, there were are limitations with this approach:

First, it cannot be fully automated, and therefore does not scale up. This is because there are no predefined, logical, or empirically or theoretically grounded values that are indicative of scoring low, medium or high on network metrics. Therefore, these boundaries have to be manually identified on a per group basis.

Second, this approach does not generalize across networks, which is for the same reason as the first issue. This means that for each network or time slice of a network, group membership has to be identified separately.

Third, our prior approach was designed for a different purpose, namely comparing the language use of certain roles in order to answer the following substantive questions: What topics are addressed by members of each group? Which topics are exclusive to a group, and which ones are shared among groups? We argued that for this purpose, the method is useful. However, in this chapter, the focus is not comparing the language use or content of groups, but on facilitating the identification of concept nodes for the enhancement of network data. For this process, the following goals were identified in the review section of this chapter:

First, identifying concept nodes not in an arbitrary fashion, but based on structural properties of the nodes that have generated, disseminated or processed the respective content. These nodes are typically social agents, such as individuals and organizations, and possibly also automated agents. For simplicity, I herein refer to them as agent nodes.

Second, adding the concept nodes (here referred to as knowledge network, which can consists of a set of unlinked nodes) to the agent nodes (here referred to as social network) such that the agents are linked through content nodes, regardless of whether these agent nodes already share a link or not. In this context, using our prior approach of identifying structurally equivalent agents implies the following limitations: taking the Funding data as an example, nodes representing the roles of formal leaders, for instance, might originate not only from different areas of the network, but also different research domains (e.g. physics, economics). Comparing their text data within and across roles helps us to identify in what areas or on what topics these people are working,

how they focus their proposals on terms related to project management or the subject matter domain, etc. – all of which are instances of role comparison. However, it does not seem reasonable to link these agent nodes to shared content nodes since it is unlikely that leaders from different fields share any content beyond generic project management terms, and terms indicating the potential for leadership, excellence and innovativeness. In fact, our prior research has shown that the strongest topic for the considered roles was project management; confirming the limitation outlined above. The same effect can even occur within a research domain, i.e. leaders emerge around different sub-fields. Another risk with linking people within a structural equivalence class is that agents could get connected to content nodes or knowledge that they were never truly exposed to, but that were simply salient in disjoint or distant parts of the overall network. In summary, enforcing knowledge nodes onto agents this way entails the risk of false positives. In conclusion, for the purpose of enhancing social networks with content nodes, it seems more reasonable to only link agent that could get exposed to the same content. Therefore, the next question is: Which grouping algorithm to employ? This question is answered in the results section based on tests in actual application domains.

6.3.2 Identify Content Nodes per Group via Topic Modeling

Topic modeling has the following properties, which help to overcome several of the aforementioned limitations of alternative approaches for extracting themes and salient terms from knowledge networks (the input to topic modeling are document-term co-occurrence matrices, which can be considered a type of knowledge network):

1. Efficient: since the learning is unsupervised, no labeled ground truth data is necessary to build a prediction model. Also, no thesauri need to be constructed.
2. Scalability: Scales up to large corpora.
3. Word sense disambiguation: can identify different meanings of a word by considering the word's context.
4. Assumed generative process: the way topic modeling is operationalized here is based on the following assumptions: groups of people generate documents by selecting topics from a pool of topics, and words per topic from a pool of words. This generative process is probabilistic, but not arbitrary.

With respect to property one, there is a lack of knowledge about the following question: How does the application of prediction models trained with supervised learning compare to the outcome of topic modeling? I am answering this question in the results section.

Topic modeling has been linked to network analysis before: Chang et al. (2009) have used the LDA) technique to suggest link labels for untyped links in semantic networks. McCallum et al.

(2007) have conducted topic modeling on all bodies from two email datasets, and comparing the resulting groups of people who are involved in the same topics. They conclude that identifying equivalence classes of people via topic modeling returns more reasonable grouping than using classic grouping methods from network analysis, and also better groupings than an alternative method for applying topic modeling on documents co-authored via people (Steyvers, Smyth, Rosen-Zvi, & Griffiths, 2004).

Mimno and McCallum (2008) argue that while in the basic version of LDA, any observed and descriptive features of the text data are generated based on an assumed latent probabilistic graphical model, conditioning topics on the observed data instead of generating the data might be more efficient. Based on this rationale, they develop the Dirichlet-Multinominal Regression (DMR) technique as an extension to LDA. The key idea with DMR is the assumption and computation of distributions per topic not only over words, but also over meta-data that provide additional information about documents. Thus, DMR eases the consideration of various types of meta-data on the text data, such as the date or publication venue of a text document.

In this chapter, I am drawing from the work mentioned above. However, with the proposed methodology, I am not learning a topical profile per individual, dyad, or document, as done in prior work, but create topical profiles conditioned on groups. Moreover, I show how the themes and terms identified with topic modeling compare to the outcome of alternative methods for extraction this information, including supervised learning. As points of comparison, I am re-using the methods that were introduced and applied in the previous chapter, including supervised learning. The advantages, limitations and some typical results of these methods on the same data as used in this chapter were already identified herein. Moreover, comparing these methods to topic modeling helps to put the outcome of this chapter into the wider context of understanding how different information and relation extraction methods relate to each other, and what different views on a network they can provide.

6.3.3 Enhance social network with the content nodes

The top N content nodes are linked to the members of the respective group. In the case of a social network, the content nodes are added such that a two-mode, agent-to-knowledge network is created. Section I in the Appendix provides a step-by-step guide for operationalizing this procedure in ORA.

6.3.4 Evaluation of Content Nodes identified with Topic Modeling

One main limitation with topic modeling is evaluation: while the underlying, probabilistic graphical model as well as the overall method for performing topic modeling are clearly defined,

the interpretation of the resulting topics is a non-standardized process. This interpretation leaves plenty of room for making sense of the outputs, or reading meaning into them (Chang, Boyd-Graber, Gerrish, Wang, & Blei, 2009). In prior work on advancing topic modeling, such as adding new parameters on which the generating of words in constrained on, people have often used datasets that they were intimately familiar with, such as their personal emails, or data that are easy to interpret, such as news wire corpora. While this is a legitimate strategy, the following questions often remain unanswered:

- Would the application of alternative information or relation extraction methods have led to the identification of the same terms and themes?
- Do the identified topics correctly represent the content of the underlying data?

In this chapter, I address the first issue by comparing the resulting topics per group to content nodes identified with alternative methods. This step is not part of the proposed methodology, but helps to validate the outcome of topic modeling via compairson.

6.4 Operationalization and Results

The proposed methodology is designed for enhancing datasets for which both, social network data as well as text data, are available. This applies to the Funding corpus (for details on this dataset see 5.3) and the Enron corpus (5.4). I also discuss the applicability of the methodology to the Sudan corpus, which contains text bodies and non-relational meta-data.

6.4.1 Application Context I: Funding Corpus

6.4.1.1 Social Network Data

For the social network, I used the collaboration networks that I created from the explicit denotation of which people were jointly funded for a grant. The construction of these networks is described in section 5.3.2.3. Given the various levels of completeness of the social networks per framework programme (FP) (Table 104) and the respective limitations as explained in 5.3.2.3, I use the networks from FP 4 to 6 for this study. The collaboration networks are weighted, directed graphs.

6.4.1.2 Grouping of Social Network Data

In order to find useful groups for the proposed methodology, I tested various grouping algorithms as implemented in the ORA software for their appropriateness. Several of these algorithms did not return results on these sizable networks (Table 104) with a decent number of groups (about 10) in a reasonable amount of time. Since the goal here is not to find an exhaustive grouping of all nodes, I reduced the social networks from the Funding data as follows: first, I

dropped all pendants, which are peripheral nodes that are linked to one other node only. Pendants can be considered as a structural equivalence class of their own that represents a certain role, i.e. the one of dependants. Also, a large number of pendants can be connected to one and the same node; resulting in marginalized power structures that may exhibit norm enforcing behavior. Next, I removed the resulting isolates. The last two steps eliminate any project teams of size two. At this point, the network data were still too large for grouping. Therefore, I reviewed the node degree distributions, which followed the skewed distribution typical for social networks, and based on this review also dropped nodes with a frequency of one. Finally, I removed resulting isolates again.

CONCOR is a classic grouping method that basically correlates the adjacencies between nodes in an iterative fashion (Wasserman & Faust, 1994). This technique is a parametric method which requires the specification of the number of groups to find a priori. Visualizing the resulting groups revealed that with CONCOR, the largest group mainly contains the collaborators on two-person projects. The second largest group mainly comprises PIs on two-person projects. The third largest group are collaborators on three-person projects, and the fourth largest one are the PIs on three-person projects. This pattern continues. These groups clearly represent meaningful structural equivalence classes. However, as discussed above, it does not seem useful to perform topic modeling on the texts per group to identify shared knowledge, since these texts might have little in common beyond the dependency structure of their contributors.

The same argument applies to the groups identified based on key entity analysis: I computed the same metrics as in the previous application scenario for the Funding data 5.3.3 on the social network, and identified the top ten agents with respect to these metrics. Visualizing the resulting network with the key entities in them suggests that they are dispersed across the graph with little cross-connectivity among them. This point further supports the previously raised concern that structurally equivalent nodes might be involved with disjoint pieces of information.

As another alternative, I used the Girvan-Newman grouping algorithm (Girvan & Newman, 2002). This algorithm basically identifies groups with strong internal connectivity, but weak connectivity to other groups. This is achieved by iteratively dropping edges with high betweenness centrality. Girvan-Newman is a non-parametric method, i.e. the number of groups to find must not, but can be pre-specified. The fundamental difference between this algorithm and the previous two grouping strategies is that Girvan-Newman mainly forms groups of nodes that can reach each other within a few steps. Based on the discussion in the methods section, this property is desirable for this project because nodes that are separated by a few links are more likely to get exposed to the same content than nodes that might have perfect structural

equivalence, but are located in disjoint components of the networks. Visualizing the resulting groups suggested that the identified group seem appropriate for this study and dataset.

As a logical follow-up on the Girvan-Newman grouping algorithm, I also tested grouping based on components, which are disjoint section of a network (Table 153). The same advantage as pointed out for Girvan-Newman also applies to components: nodes within a component have a higher chance of getting exposed to the same information by either working on a grant together and/ or via information diffusion through the wider network than structurally equivalent nodes from different components. Visualizing the resulting groups showed that they are very similar to the ones found with Girvan-Newman, and are often identical for small groups (about ten members and less). The difference is that Girvan-Newman occasionally finds sub-groups within large components, which are less deterministic than the groups just based on components.

In summary, considering the limitations and advantages outlined in this section together with the requirements and goals for the proposed methodology, I decided to use the Girvan-Newman algorithm for grouping social networks.

Table 119 shows the number and size of groups obtained per FP considered. Across all FPs, most groups have a size of two. Many of these groups are actual project teams, where the members are involved in the same proposal. For this study, I am focusing on less deterministic groups that may and in fact in many cases do involve multiple proposals.

Table 119: Number and size of networks and groups

Data	Raw			Groups			Number of groups					
	Nodes	Edges	Texts	Nodes	Edges	Modularity	Number	Min	Max	Average	Std Dev	10+ nodes
FP4	35,061	34,583	9,651	373	262	0.97	120	2	21	3.1	2.8	5
FP5	34,541	48,670	12,669	1016	1118	0.80	188	2	147	5.4	13.4	13
FP6	39,848	43,033	9,184	649	441	0.99	210	2	13	3.1	1.9	3

6.4.1.3 Identify Content Nodes per Group via Topic Modeling

For each FP and each group, I extracted all proposals that each member of the group was a PI on. This can entail proposals that group members have authored with others outside the group. I made this design choice to account for the possibility that the group might still benefit from this knowledge, or this knowledge can diffuse through the group.

LDA takes text by concept matrices as an input. In order to generate these matrices, I performed semantic network extraction in AutoMap by considered all tokens as concepts except for entries specified in the delete list used throughout the previous chapter. For link formation, I used

windowing with a window size of seven (this method and choice of window size are explained in the previous chapter).

Next, I conducted topic modeling on the semantic networks in ORA: I ran pretest with different numbers of topics (5, 10, 20), and based on that decided to use ten topics for FPs 4 and 6, and 20 for FP5. Additional parameters that need to be set relate to the Gibbs sampling method. In consultation with Aparna Gullapalli, who developed the LDA routine in ORA, I initially selected the following parameter values: step size: 100, iteration rate: 2,000, beta-value: 0.5. Inspecting the resulting topics showed that many of them involved numerical values, which seemed mainly noisy. Therefore, I re-generated the semantic networks as described above, but also removed numericals from the data.

Inspecting the networks again revealed that multiple runs with the same parameter configuration returned different topics and topic members. This is no surprise since Gibbs sampling is a probabilistic method that uses random seeds, so that results may vary across runs. However, with a sufficiently larger iteration rate, the membership probability per topic should converge. I further explored this issue by increasing the number of topics to 30 and the iteration rate to 5,000. I used this modified configuration (the other parameters were kept constant and at the values as shown above) to perform three topic modeling runs each on a small, a medium size and a large semantic network from the Funding data, and compared the results across runs per network. This process confirmed the previous observation, i.e. that topics and members differ across runs with identical parameter settings. Table 120 shows an example for the first five topics for a small network with an iteration rate of 2,000. There, the green cells indicative duplicate entries from different runs – what we are hoping for here is a high amount of green cells per run. While robustness of topic modeling is no requirement for the proposed methodology, some coherence is needed for two reasons: first, to overcome the arbitrariness of finding content nodes, which is a limitation of alternative methods for enhancing social networks with content nodes. Second, to ensure the reproducibility of the results presented in this document. For these reasons, I tested whether LDA-based topic modeling as implemented in the Mallet package leads to more robust results (A. K. McCallum, 2002). Table 121 shows the top five topics for the same network as used for Table 120. To produce these results, I generated ten topics with ten members. The results indicate two things: first, there is a higher overlap of topic membership (green cells) across runs on the same data with the same parameters with Mallet. Second, LDA in ORA and Mallet retrieve very different themes and terms. The results from Mallet suggest that the text data are about transportation and policy, while with ORA, it seems hard to identify an overarching theme for the retrieved terms. However, without any solid validation based on ground truth data, it cannot be said which implementation retrieves more

appropriate results. All that can be concluded from this limited, qualitative comparison is that the results from Mallet are more robust. For this reason only, Mallet was used for further analysis. Finally, I tested various numbers of topics to generate with Mallet (10, 20, 30, 50), and decided to stick to the initial number of ten for FP4 and 6, and 20 for FP5.

Table 120: Topic groups for FP4, node group 1 (LDA in ORA)

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Run 1	urban	chains	concentrates	investments	compared
	investigated	derive	ddg	barrier	dysaf
	co-ordinated	inter-operability	east-west	covering	consideration
	innovations	foresee	calibration	addressing	developed
	co-ordination	innovations	impulse	behaviours	appended
	20040101…	maintenance	bottlenecks	rail-ten	measure
	auspices	purpose	draw	interfaces	ballasted
	corridors	assist	sensitivity	20040101_14…	backcasting
	links	defining	urban	degree	apricot
	handbook	allowing	contribution	contradictory	
Run 2	professional	eastern	20040101…	compete	criteria
	conduct	databases	forms	central	players
	ground-based	fulfilment	documented	disseminated	varying
	derive	links	aim	seagoing	margin
	nox	corresponding	collected	allow	bundles
	operated	meet	arrangements	20040101…	20040101…
	easy-to-use	effect	aims	foresee	axes
	deliverable	preliminary	observatory	temporality	fifth
	committee	degradation	maintenance	harmonisation	advanced
	found	rd	conceive	centres	structures
Run 3	low	extended	covering	bft	appendices
	issue	effect	alps	aggregation	databases
	efficient	fasteners	prototype	aimed	freight
	sensitivity	consistent	20040101…	20040101…	commission
	evident	applicable	20040101…	acceptance	describe
	calibrate	devoted	by-road	analyze	southampton
	competitive	produces	collecting	corridors	follow-ups
	examples	eastern	track	bridges	integrates
	lisbon	capacities	unfold	co-operation	core
	accessibility	deliverables	administrations	deals	intermodal

Table 121: Topic groups for FP4, node group 1 (LDA in Mallet)

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Run 1	policy	transport	transport	transport	intermodal
	methodology	project	scenarios	road	transport
	projects	european	development	freight	quality
	strategic	system	study	sea	freight

	assessment	economic	pricing	costs	market
	research	cost	relevant	project	actors
	european	freight	work	infrastructure	decision
	develop	infrastructure	eu	systems	services
	transport	improvements	countries	european	traffic
Run 2	policy	transport	transport	transport	intermodal
	projects	european	data	freight	transport
	programme	system	scenarios	sea	project
	assessment	project	methodology	project	chains
	strategic	economic	mobility	costs	quality
	research	interoperability	evaluation	urban	freight
	transport	research	pilot	services	traffic
	methodology	infrastructure	model	european	examine
	european	freight	demonstration	infrastructure	case
Run 3	transport	programme	policy	data	intermodal
	project	research	task	transport	transport
	system	policy	methodology	scenarios	monitoring
	european	assessment	ctp	mobility	network
	economic	strategic	strategic	models	european
	market	european	project	pricing	information
	cost	level	european	development	freight
	development	development	level	model	making
	analysis	based	modelling	applications	studies

6.4.1.4 Alternative Text Analysis Methods as Point of Reference for Evaluation

Several methods against which the themes and terms identified by topic modeling can be compared are available: in the simplest case, one could identify salient terms from the text bodies by computing metrics that represent (weighted) term frequencies, such as tf*idf. Since this thesis is about relational representations of information from texts, I disregard this option, and focus on networks constructed from text data instead:

First, for each FP and considered group, I create knowledge networks from the meta-data in the Funding corpus as described in 5.3.2.3. Once the meta-data have been organized e.g. in a database, this approach is about as fast as performing LDA on the texts per group. The entities in the meta-data networks can be considered as a type of ground truth data because they are key words and index terms that were selected by the people who submitted the proposal, and originate from a mixture of pre-defined and self-defined categories that are meant to best represent the gist of a text. Table 122 shows the size of the comparison networks.

Second, I extracted semantic networks from the text bodies by using the Data to Model (D2M) process as described in section 5.3.2.2.. This process requires a thesaurus. If such a thesaurus has already been generated, evaluated and refined, which is the case here; extracting knowledge

networks this way also becomes efficient. I reused the refined, auto-generated Funding thesaurus for this purpose; considering all entries as knowledge. This strategy allows for extracting semantic networks instead of meta-networks. Based on inspection of the semantic networks, I removed a few more overly generic concepts from the thesaurus[23], and regenerated the networks.

Table 122: Size of comparison networks

Data	Groups		Meta-data		D2M+EE	
	Number of members	Number of texts	Nodes	Edges	Nodes	Edges
FP4, group1	21	43	38	169	722	5,521
FP4, group2	16	37	49	246	771	5,278
FP4, group3	13	31	25	111	710	4,980
FP5, group1	147	1,105	209	2,458	3,624	99,960
FP5, group2	85	761	211	2,505	3,047	79,252
FP5, group3	45	534	206	2,364	2,890	60,238
FP6, group1	13	17	66	691	553	3,534
FP6, group2	11	17	84	924	462	2,302
FP6, group3	11	12	60	591	387	1,896

Once these alternative network data are generated, there are several ways for identifying content nodes from them: first, key entity analysis (described in section 5.2.3) can be conducted. This approach has been used in the past for locating content nodes to enhance social network data with (described in section 6.1.5.1). To show how the results obtained with topic modeling compare to this common prior method, I selected this approach for this study.

Alternatively, grouping methods could also be applied to these comparison networks in order to identify groups of structurally similar content nodes. In contrast to key entity analysis of knowledge networks, this approach has not yet been used in this thesis, such that limitations, advantages and typical outcomes of this method in the contexts of this thesis and datasets are unknown. Also, this approach is not typically used in practical applications. For these reasons, I decided to focus on key entity analysis as a point of comparison.

6.4.1.5 Results and Evaluation

There are 120-210 groups per framework program. In order to identify the topics and topic members for the set of texts per groups, and comparing these results to knowledge nodes identified with alternative methods, I decided to focus on the three largest groups for FP 4 to 6. Table 122 shows the size of these groups in terms of members and number of texts. In Table 123 to Table 140, for each group, the following information is presented:

[23] The removed entries are: 3, 4, including, main, aims, aim.

- For topic modeling, the eight most prevalent topics and up to nine topic members[24]. The topics are sorted from left to right by decreasing values of the Dirichlet parameter, which indicates the likelihood of a topic among the retrieved topics. Green cells indicate entities that were also found with key player analysis on the comparison networks.
- For the comparison networks, the ten key nodes according to previously introduced network metrics. Green cells indicate terms that are also found among the topic members.

In all results Tables, some terms were abbreviated[25] to accommodate to the real estate on the pages. Each page contains the topic modeling output in the upper table, and the results from key entity analysis of both types of comparison networks in the lower tables.

Comparing the results across all three information extraction methods suggests the following:

1. There is a minimal intersection between the key entities from meta-data knowledge networks and topic members from topic modeling. This can be partially explained with the fact that the terms in the meta-data are often multi-word combinations of key words, e.g. “sustainable mobility” or “integration of new technology”, while the employed implementation of topic modeling retrieves unigrams.

2. When reading through the members per topic (topic modeling), the terms do sound related, but it was often hard for me to come up with a good label for a topic. In the past, people who encountered the same difficulty had suggested to use the strongest word per topic for that label. Looking at the topics and the key entities from the meta-data network *together*, the highest rank key entities often seems to be highly fitting labels for some of the topics. Here are some examples: in FP6, group 1 (Table 136), the first five topics seem to be about airplanes. For the same data, the key entity from the meta-data networks is “aerospace technology”, which could serve as an appropriate label for these topics. In FP5, group 3 (Table 133), topics 3, 5, and 6-8 seem to be about climate and water. The top entity from the meta-data networks is “environmental protection”. In FP 6, group 3 (Table 140), topics 1-4 and 6 are about tools and products. The corresponding key entity from the meta-data network is “industrial manufacturing”.

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[24] I had planned to retrieve ten members per topic, but in Mallet, the desired number of terms per topic need to set to one more than the number that is retrieved. I only noted this limitation after completing this study.

[25] Abbreviations used in table: method. = methodology, develop. = development, tech. = technology, technologies, reg. = regional, interoper. = interoperability, europe. = European, environment. = environmental, info. = information, comm. = communication, transport. = transportation, product. = production, assess. = assessment, apps. = application, applications, manufac. = manufacturing, manufacture, protect. = protection, integrate. = integration, org. = organization, _the_ = _, construct. = construction, intermod. = intermodal, improve. = improvement, monitor. = monitoring, assemble. = assembling

3. In topic modeling, while some highly salient terms from the underlying text data occur in multiple topics, most other members appear in one topic. In contrast to that, in the meta-data networks and networks extracted from text bodies (in the following referred to as text-based networks), each entity can occur only once per metric, but across metrics, the overlap in entities is large. Moreover, for both types of comparison networks, the ranking of entities that occur for multiple metrics is similar per network construction methods, especially for highly ranked entities.

5. Most of the key entities found in the text-based networks also occur among topic members from across multiple topics. This is true for generic terms from the domains of science and research, e.g. “method”, “training” and “integration”, but also for domain specific terms. However, this relationship between text-based networks and topic modeling is asymmetric, i.e. the topic modeling outputs contain many terms that do not occur in the text-based networks. I further analyzed this set of terms, and found out that many of them were originally contained in the auto-generated, refined thesaurus, but removed as part of the cleaning process, e.g. “main”, “aims”, “objective”, and “activities”. I had removed these terms from the auto-generated thesaurus to exclude entities that are overly generic in this dataset and domain. Using the raw, auto-generated thesaurus might have resulted in a higher overlap, but not in more useful network data extracted from the texts. Taking this argument one step further, I suggest that topic modeling; an unsupervised prediction technique, might benefit from the same cleaning techniques that are appropriate for the output of supervised prediction techniques used on the same data.

6. Discounting for noise terms in topic modeling, the unsupervised prediction approach (topic modeling) and the supervised prediction approach (entity extraction, trained on different data) applied to the same data result in the retrieval of similar terms. The fact also partially explains the next finding.

7. In contrast to the key entities from the meta-data networks, the top key entities from the text-based networks would not be useful labels for topics.

8. The key entities in the meta-data and text-based networks are highly similar across the considered metrics per network type. Especially total degree centrality and clique count return similar results, while betweenness centrality provides an additional set of entities.

Table 123: Topics for FP4, group 1

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
0.25	0.12	0.11	0.08	0.07	0.04	0.03	0.02
policy	transport	transport	transport	projects	intermod.	noise	transport
strategic	europe.	intermod.	data	programme	pre	freight	monitor.
research	project	freight	scenarios	evaluation	transport	track	research
europe.	market	road	mobility	transport	formulas	wagons	centers
method.	objective	project	develop.	project	terminal	traffic	network
project	interoper.	identify	method.	develop.	number	silent	decision
tasks	economic	europe.	pricing	rtd	improve.	europe.	assemble.
ctp	systems	operators	main	framework	policy	low	europe.
level	cost	traffic	socio	options	europe	project	system

Table 124: Key entities for FP4, group 1

Meta-Data				D2M+EE			
Degree centrality	Between. centrality	Eigenvector centrality	Clique count	Degree centrality	Between. centrality	Eigenvector centrality	Clique count
transport	transport	transport	transport	transport	transport	transport	transport
reg._develop.	construct._tech.	reg._develop.	reg._develop.	project	project	europe.	project
construct._tech.	reg._develop.	construct._tech.	construct._tech.	europe.	freight	freight	europe.
safety	policies	safety	safety	freight	projects	infrastructure	method.
policies	sustainable_mobility	policies	policies	model	europe.	intermod.	intermod.
strategic_research	safety	strategic_research	ind._manufac.	intermod.	infrastructure	project	freight
integrate._of_new_tech.	air_transport	integrate._of_new_tech.	economic_aspects	infrastructure	effects	systems	model
tech._transfer	economics_of_transport_systems	tech._transfer	microelectronics	method.	model	monitor.	projects
innovation	quality_of_network	innovation	transports	astra	intermod.	passenger	infrastructure
system_org._and_interoper.	transport_management	system_org._and_interoper.	electronics	projects	criteria	method.	design

Table 125: Topics for FP4, group 2

0.20	0.18	0.14	0.10	0.08	0.06	0.05	0.04
policy	transport	transport	wp	research	dissemination	iea	policy
method.	europe.	urban	develop.	cities	info.	road	scenarios
assess.	public	travel	traffic	europe.	programme	develop.	corridor
define	user	policy	areas	results	project	models	range
project	issues	public	environment.	work	transport	integrated	actions
strategic	potential	uk	decision	case	target	environment.	assess.
projects	users	assess	tools	involve	based	order	countries
ctp	groups	identify	impact	project	aims	lifestyles	economic
task	objective	local	socio	key	impact	project	develop.

Table 126: Key entities for FP4, group 2

Meta-data				D2M+EE			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centrality**	**Between. centrality**	**Eigenvector centrality**	**Clique count**
transport	transport	transport	transport	transport	transport	transport	transport
reg._develop.	construct._tech.	reg._develop.	safety	strategies	project	strategies	europe.
construct._tech.	policies	construct._tech.	reg._develop.	europe.	europe.	optimal	project
safety	safety	safety	construct._tech.	project	strategies	europe.	strategies
policies	tech._transfer	policies	policies	method.	cities	sustainable	public_transport
tech._transfer	reg._develop.	strategic_research	tech._transfer	cities	eu	rtd	cities
innovation	info._systems	tech._transfer	innovation	public_transport	framework	project	travel
strategic_research	environment._protect.	innovation	environment._protect.	sustainable	public_transport	cities	eu
economic_aspects	industrial_manufac.	integrate._of_new_tech.	economic_aspects	optimal	processes	projects	method.
integrate._of_new_tech.	innovation	economic_aspects	microelectronics	projects	tools	europe	projects

Table 127: Topics for FP4, group 3

0.38	0.15	0.11	0.09	0.08	0.07	0.07	0.06
safety	vts	info.	transport	disc	accident	wp	traffic
project	system	traffic	shipping	demonstration	evacuation	navigation	task
maritime	network	vessel	short	eu	model	gnss	situation
ship	info.	services	sea	training	design	based	develop
transport	project	action	conditions	vii	main	inland	scenarios
assess.	evaluation	vts	test	scenarios	evaluation	info.	comm.
human	comm.	projects	interface	integrated	range	vii	work
operational	processing	users	transport.	control		image	design
related	epto	operators	complete	purposes		radar	obstacles

Table 128: Key entities for FP4, group 3

Meta-Data				**D2M+EE**			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centrality**	**Between. centrality**	**Eigenvector centrality**	**Clique count**
transport	transport	transport	transport	vts	vessel	management	vts
reg._develop.	ports_and_logistics)	reg._develop.	reg._develop.	vessel	vts	vessel	transport
construct._tech.	inland_navigation	construct._tech.	construct._tech.	management	transport	services	services
safety	reg._develop.	safety	safety	transport	project	transport	maritime
safety_and_environment_protect._in_maritime_operations	policies	safety_and_environment_protect._in_maritime_operations	policies	eu	services	eu	vessel
efficiency	construct._tech.	efficiency	microelectronics	services	maritime	vts	project
environment._protect.	transports	environment._protect.	industrial_manufac.	project	training	dg	ship
economic_aspects	safety	economic_aspects	electronics	maritime	ship	concept	management
policies	maritime_transport_(shipping	policies	maritime_transport_(shipping	ship	europe.	management_and_info._services	training
maritime_transport_(shipping	telematics_app.s_for_transport	maritime_transport_(shipping	ports_and_logistics)	training	eu	systems	europe.

Table 129: Topics for FP5, group 1

0.76	0.20	0.11	0.09	0.08	0.08	0.07	0.06
project	research	europe.	management	cell	climate	health	product.
develop.	europe.	social	biodiversity	gene	data	clinical	food
develop	network	policy	sustainable	molecular	ocean	disease	treatment
data	info.	economic	land	cells	models	risk	material
based	eu	eu	europe	expression	carbon	control	waste
results	international	countries	environment.	genes	chemical	europe	products
environment.	workshops	public	water	disease	europe.	food	mesh
provide	activities	policies	forest	protein	time	treatment	water
quality	scientific	develop.	conservation	mechanisms	model	diseases	gauge

Table 130: Key entities for FP5, group 1

Meta-Data				D2M+EE			
Degree centrality	Between. centrality	Eigenvector centrality	Clique count	Degree centrality	Between. centrality	Eigenvector centrality	Clique count
environment._protect.	training	environment._protect.	economic_aspects	project	project	management	project
life_sciences	policies	life_sciences	scientific_research	europe.	europe.	fisheries	europe.
economic_aspects	environment._protect.	economic_aspects	environment._protect.	management	europe	europe.	management
scientific_research	education	fisheries	social_aspects	fish	analysis	project	fish
fisheries	renewable_sources_of_energy	resources_of_sea	policies	fisheries	study	fish	studies
resources_of_sea	tech._transfer	agriculture	regulations	analysis	network	aquaculture	analysis
health	social_aspects	food	legislation	eu	eu	sustainable	models
medicine	reg._develop.	resources_of_sea_fisheries	renewable_sources_of_energy	species	studies	species	model
agriculture	scientific_research	key_action_sustainable_agriculture	meteorology	models	model	eu	fisheries
policies	transport	fisheries_and_forestry	life_sciences	methods	systems	marine	eu

Table 131: Topics for FP5, group 2

0.84	0.45	0.25	0.18	0.11	0.08	0.07	0.07
project	project	europe.	policy	materials	energy	system	system
develop.	models	network	environment.	material	power	fuel	based
tech.	data	research	economic	components	system	energy	monitor.
product.	model	projects	policies	high	renewable	power	tool
process	results	knowledge	energy	process	pv	heat	optical
high	tools	eu	impacts	parts	systems	cell	control
cost	analysis	activities	sustainable	coatings	solar	hybrid	machine
systems	test	info.	develop.	manufac.	market	cooling	software
develop	based	countries	framework	composite	integrate.	efficiency	refurbishment

Table 132: Key entities for FP5, group 2

Meta-data				D2M+EE			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centrality**	**Between. centrality**	**Eigenvector centrality**	**Clique count**
economic_aspects	standards	economic_aspects	economic_aspects	project	project	project	project
environment._protect.	evaluation	environment._protect.	environment._protect.	europe.	europe.	energy	systems
scientific_research	environment._protect.	innovation	scientific_research	energy	systems	systems	design
industrial_manufac.	social_aspects	industrial_manufac.	social_aspects	systems	energy	design	energy
renewable_sources_of_energy	renewable_sources_of_energy	safety	policies	design	europe	europe.	europe.
energy_saving	policies	tech._transfer	regulations	tools	eu	tools	performance
social_aspects	reg._develop.	materials_tech.	legislation	models	tools	tech.	models
tech._transfer	fisheries	energy_saving	energy_saving	analysis	models	advanced	tech.
innovation	tech._transfer	renewable_sources_of_energy	renewable_sources_of_energy	fuel	analysis	analysis	advanced
safety	other_energy_topics	key_action_innovative_products	other_energy_topics	tech.	app.s	fuel	tools

Table 133: Topics for FP5, group 3

0.80	0.16	0.11	0.09	0.08	0.07	0.07	0.07
project	research	climate	policy	coastal	ozone	water	materials
provide	europe.	models	urban	marine	chemical	ecosystems	tech.
based	network	model	economic	mediterranean	atmospheric	management	industrial
results	social	data	decision	sea	climate	biodiversity	high
develop.	access	ocean	develop.	water	impact	community	process
develop	info.	sea	air	ecosystem	aerosol	natural	product.
systems	europe	variability	mountain	product.	emissions	europe	efficiency
developed	activities	system	policies	species	atmosphere	species	cost
info.	national	atmospheric	eu	waters	processes	fishing	develop.

Table 134: Key entities for FP5, group 3

Meta-data				**D2M+EE**			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centrality**	**Between. centrality**	**Eigenvector centrality**	**Clique count**
environment._protect.	environment._protect.	environment._protect.	scientific_research	project	project	project	project
economic_aspects	policies	fisheries	economic_aspects	europe.	europe.	europe.	europe.
scientific_research	social_aspects	resources_of_sea	environment._protect.	models	europe	models	model
fisheries	scientific_research	forecasting	social_aspects	model	analysis	model	models
resources_of_sea	standards	mathematics_statistics	policies	analysis	models	expected	analysis
social_aspects	education_and_training	meteorology	regulations	systems	model	modeling	systems
life_sciences	industrial_manufac.	measurement_methods	legislation	europe	studies	approach	europe
meteorology	info._processing	climate_and_biodiversity	meteorology	management	novel	impacts	modeling
measurement_methods	renewable_sources_of_energy	key_action_global_change	renewable_sources_of_energy	ozone	systems	management	understanding
forecasting	reg._develop.	economic_aspects	life_sciences	studies	study	systems	studies

Table 135: Topics for FP6, group 1

0.26	0.11	0.07	0.07	0.06	0.04	0.04	0.03
engine	aircraft	tbc	turbine	noise	industry	project	process
low	concepts	control	engine	broadband	automotive	research	equipment
noise	capabilities	provide	cfd	methods	innovative	field	significant
aircraft	future	key	aero	prediction	tech.	europe	supply
vital	integrate.	tech.	aggressive	research	range	goals	breakthrough
tech.	assess.	aero	technical	fan	methods		
engines	impact		high	understanding	low		
fan			environment	programmes	provide		
weight			goal	universities			

Table 136: Key entities for FP6, group 1

Meta-data				D2M+EE			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centrality**	**Between. centrality**	**Eigenvector centrality**	**Clique count**
aerospace_tech.	propulsion	aerospace_tech.	aerospace_tech.	noise	project	noise	noise
measurement_methods	aerospace_tech.	forecasting	forecasting	low	aircraft	low	engine
mathematics_statistics	evaluation	mathematics_statistics	mathematics_statistics	engine	noise	fan	aircraft
forecasting	environment._protect.	measurement_methods	measurement_methods	aircraft	engine	engine	methods
innovation	cooperation	tech._transfer	industrial_manufac.	fan	europe.	broadband	design
tech._transfer	systems_approach_to_future_efficient	policies	tech._transfer	tech.	advanced	aircraft	project
policies	industrial_manufac.	innovation	policies	project	methods	turbo	industry
economic_aspects	social_aspects	social_aspects	innovation	europe.	industry	concepts	advanced
social_aspects	coordination	evaluation	economic_aspects	methods	improved	tech.	tech.
evaluation	policies	economic_aspects	environment._protect.	design	novel	weight	low

Table 137: Topics for FP6, group 2

0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.01
europe.	control	track	risk	noise	industrial	samco	bridge
research	vibration	methods	building	vehicles	system	international	high
transport	adaptive	network	develop.	measures	systems	structural	market
integrated	impact	project	assess.	impact	assess.	field	modtrain
system	design	countries	tech.	approaches	monitor.	thematic	product
tech.	landing		design	control	objective		tech.
systems	shock		activities		safety		
objective	structural				risk		
services	full					integrated	

Table 138: Key entities for FP6, group 2

Meta-data				D2M+EE			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centrality**	**Between. centrality**	**Eigenvector centrality**	**Clique count**
innovation	industrial_manufac.	tech._transfer	tech._transfer	design	design	network	design
tech._transfer	construct._tech.	innovation	innovation	network	systems	operators	components
policies	evaluation	policies	scientific_research	structural	bearings	eight	energy
environment._protect.	transport	environment._protect.	policies	methods	integrated	project	systems
scientific_research	environment._protect.	energy_saving	industrial_manufac.	systems	europe.	function	building
energy_saving	safety	renewable_sources_of_energy	measurement_methods	europe.	advanced	validation	structural
renewable_sources_of_energy	measurement_methods	fossil_fuels	evaluation	infrastructure	project	europe	bearings
fossil_fuels	media	other_energy_topics	forecasting	solutions	performance	infrastructure	integrated
other_energy_topics	policies	scientific_research	environment._protect.	project	road_transport	railways	europe.
industrial_manufac.	tech._transfer	fisheries	energy_saving	integrated	energy	db	adaptive

Table 139: Topics for FP6, group 3

0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01
tooling	micro	particles	industrial	kmm	product.	coated	tactile
adjustable	products	products	forging	integrate.	demands	sheet	neural
manufac.	manufac.	project	virtual	training	manufac.	polymer	virtual
tech.	mass	develop	knowledge	micro	integrate.	develop	sensors
forming	tech.	objective	materials	europe.		systems	based
innovative	systems	integrate.	processes			products	products
project	integrated	micro	create				
	training		related				
	develop		integrate.				

Table 140: Key entities for FP6, group 3

Meta-data				D2M+EE			
Degree centrality	**Between. centrality**	**Eigenvector centrality**	**Clique count**	**Degree centr.**	**Between. centr.**	**Eigenvector centr.**	**Clique count**
industrial_manufac.	industrial_manufac.	industrial_manufac.	industrial_manufac.	tooling	design	tooling	tooling
tech._transfer	tech._transfer	innovation	aerospace_tech.	virtual	products	materials	design
innovation	biotech.	tech._transfer	forecasting	design	micro	virtual	products
innovation_tech._transfer	new_and_user-friendly_product._equipment_and_tech.	innovation_tech._transfer	mathematics_statistics	materials	tech.	simulations	processes
materials_tech.	aerospace_tech.	materials_tech.	measurement_methods	micro	europe.	processes	key
and_their_incorporation_into_factory_of_future	cooperation	cooperation	tech._transfer	processes	tooling	led	tools
coordination	and_their_incorporation_into_factory_of_future	and_their_incorporation_into_factory_of_future	innovation	products	project	design	led
new_and_user-friendly_product._equipment_and_tech.	based_on_nanotech._and_new_materials	coordination	scientific_research	europe.	advanced	key	materials
cooperation	measurement_methods	new_and_user-friendly_product._equipment_and_tech.	innovation_tech._transfer	led	processing	testing	advanced
aerospace_tech.	coordination	biotech.	materials_tech.	knowledge	led	products	europe.

6.4.2 Application Context II: Enron Corpus

6.4.2.1 Social Network Data

For the social networks, I re-used the communication networks that I had constructed from the Enron email headers as described in section 5.3.2.3. For information about the considered time periods and sizes of the networks see Table 113. The communication networks are weighted, directed graphs.

6.4.2.2 Grouping of Social Network Data

From the communication networks, I also removed isolates, since they would only form groups of their own or with other isolates. Furthermore, I dropped loops, which happen if people copy or blindcopy themselves on an email. I did not remove pendants, which for these data are people who only receive emails, but did not send an email to anybody in the considered sample. However, in the context of covert networks, people who only receive information have shown to be highly relevant: when planning and executing illicit activities, the need to conceal is higher than the need to coordinate (Baker & Faulkner, 1993). Consequently, people tend to keep their communication volumes low (Klerks, 2001).

The social networks from the Enron data are denser than the Funding networks. This is partially due to the chosen data construction mechanism: the Funding data are star network structures around PIs, while in Enron, any email sent or received by the people in the CASOS Enron database are represented as a link.

In contrast to the Funding data, for the Enron networks, CONCOR groups were not mainly based on the number of emails that people have sent or received. However, the members within CONCOR groups again typically did not share direct connections, but were spread across the network. Therefore, the same argument as made before, namely that enforcing shared content onto these group members seems to be an inappropriate strategy as it results in false positive links.

Due to the comparatively high network density, the Girvan-Newman algorithm finds less distinct groups in the Enron networks than in the Funding networks. In fact, without any network post-processing, the vast majority of nodes gets places into one group, and also into one component. In order to explore whether removing low-weight nodes can help with this issue, I identified meaningful cut-off values for the links to disregard for grouping: I inspected the in-degree and out-degree distribution of the networks (Figure 14, Figure 15); realizing that they do not follow a power law distribution. This means that it is not the case that most people have a low email volume, especially not for emails received. Since this observation is a counterargument to the

previous point that people involved in illicit activities keep their communication volumes low, it further supports the previously emphasized fact that much of the conversation and many of the people in Enron had nothing to do with any illicit activities.

Figure 14: Distribution of emails sent

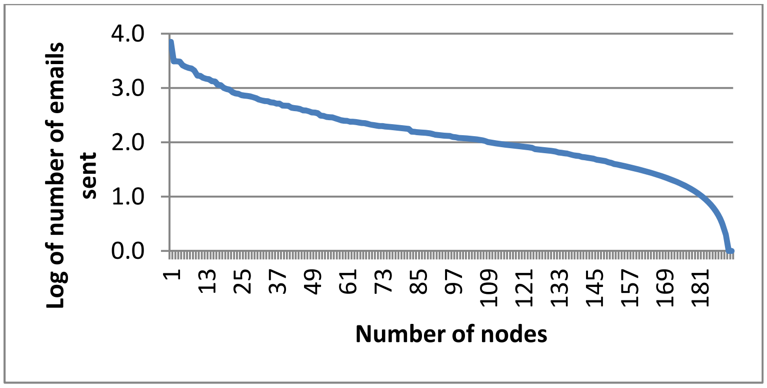
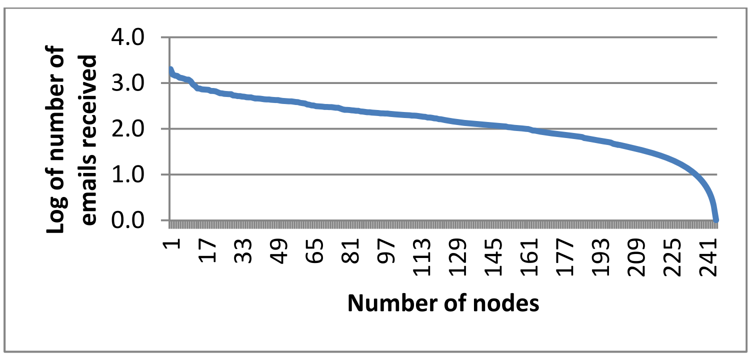


Figure 15: Distribution of emails received



Further inspecting the link frequency distributions, I decided to drop emails links with a frequency of less than 16. Applying Girvan-Newman again did result in multiple groups, but visually inspecting them in ORA suggested that the larger groups still had sub-structures that Girvan-Newman did not pick up on yet. Therefore, for each of the three networks, I increased the number of Girvan-Newman groups one by one, visually inspected the resulting partitioning, and identified the most appropriate number of groups through this visual analytics procedure. Figure 16 shows an example of this process; displayed are the final groups for time period 1 (groups are indicated by the green circle, that holds the group members together). Next, I passed this number as a parameter to the Girvan-Newman algorithm. Comparing the resulting groups showed that they coincided with the groups identified in the visualizer.

Table 141 shows the number and size of groups per time period considered. Overall, groups in these data center on people who sent one or more emails to many others. While these groups can

also be retrieved by extracting the ego-network of key entities that score highest on node centrality metrics, the small, disjoint groups would be missed with this alternative approach.

Figure 16: Example for Girvan-Newman groups in Enron, time period 1

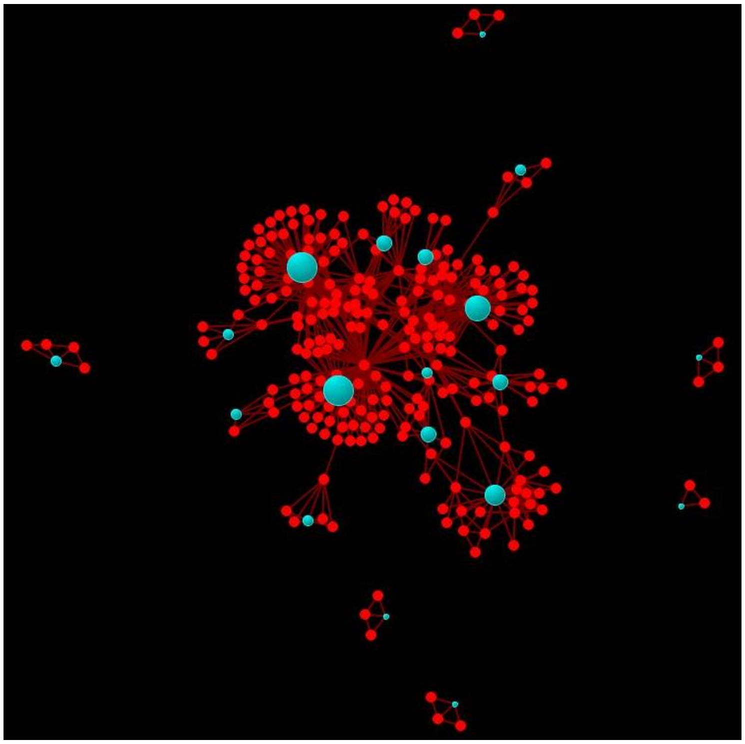


Table 141: Number and size of networks and groups

Data	Raw			Groups			Number of groups					
	Nodes	Edges	Emails	Nodes	Edges	Modularity	Count	Min	Max	Average	Std Dev	10+ nodes
Period 1	448	3,092	6,901	238	498	15.3	19	2	48	12.5	14.1	7
Period 2	433	2,295	3,711	151	234	24.4	11	2	66	13.7	20.6	3
Period 3	435	4,721	11,042	322	1,099	22.4	10	8	124	32.1	35.3	8

6.4.2.3 Identify Content Nodes per Group via Topic Modeling

For each group, I retrieved the emails sent among members of the groups. This design decision deviates from the Funding data, where I also considered proposals that PIs had authored with people outside the group since the group might still benefit from this expertise. However, email data is more private, and it is not a given that a group has access to the knowledge that a group members shares with somebody outside the group.

For topic modeling in Mallet, I again explored different numbers of topics. This time, I requested the top eleven terms in order to get the top ten terms. For all other parameters, I used the same

settings as for the Funding data. Based on my screening and comparison of the results, I decided to generate the numbers of topics as shown in Table 142. One reason for why the number of potentially useful topics does not linearly increase with the number of texts is that the same email might occur in multiple people's inboxes, e.g. when somebody forwarded an email or sent on email to multiple recipients.

6.4.2.4 Alternative Text Analysis Methods as Point of Reference for Evaluation

For the Enron data, we have no meta-data available that can serve as a point of comparison. Therefore, I only extracted networks from the email bodies per group and time period as follows: I re-used the refined, auto-generated Enron thesaurus as part of the D2M text coding process. Since we only need knowledge node here, and topic modeling does not differentiate between different node classes either, I converted all but the attribute entries in the thesaurus to be associated with the knowledge class. Also, I removed a few more numerical entries (all numbers from 1 to 150) that should have been classified as attributes. The resulting thesaurus had 6,227 entries. Table 142 shows the number of nodes in the groups and comparison networks. Both, topic modeling and key entity analysis are based on the exact same text data.

Table 142: Size of groups and comparison networks

Data		Social Network		Topics	D2M+EE	
Time Period	Group	Members	Texts		Nodes	Edges
1	1	48	189	15	612	2,090
1	2	44	133	15	581	1,430
1	3	33	442	20	1,388	9,786
2	1	66	240	15	867	2,626
2	2	33	1,212	25	4,068	44,370
2	3	28	489	20	1,151	5,622
3	1	124	1,931	25	2,025	14,026
3	2	51	418	20	1,146	6,052
3	3	37	437	20	1,101	5,176

6.4.2.5 Results and Evaluation

To stay consistent with the approach to data analysis and evaluation used for the Funding data, I analyze the top three groups per time period again. The same network metrics as used for the comparison networks from the Funding data are employed again for the text-based networks. However, in order to provide some additional information about the relationship between topic modeling and key entities from text-based networks, I use a different way of presenting the results: Table 143 to Table 151 each show the outcome of both methods; containing the following:

- The first block are the terms identified by both, topic modeling and key entity analysis of the text-based networks. The comparison is based on the top ten topics from topic modeling, and the top ten key entities from the text-based networks.
- The second block lists the entities found with key entity analysis of the text networks.
- The third block shows the topics and members not found in the comparison network.

The following results from the Funding study can be confirmed with the results from this study:

1. Most of the key entities from the text-based networks are also retrieved with topic modeling. This is true for generic terms from the domain and dataset, e.g. “Enron” and instances of the time entity class, as well as specific terms. This relationship between text-based networks and topic modeling is asymmetric: the topic modeling outputs contain many terms that do not occur in the text-based networks, but this might be mainly due to the limited number of key-entities retrieved.

2. Further analyzing the terms found with topic modeling, but not key entities analysis shows that many of these terms were originally in the auto-generated, refined thesaurus, but eliminated as part of the thesaurus cleaning process, e.g. “pmto” and “amto”. I had removed these entities from the thesaurus to exclude overly generic terms given the dataset and domain. Using the raw thesaurus might have resulted in a higher overlap, but not in more useful networks.

3. After disregarding noise terms from topic modeling, the unsupervised and the supervised prediction methods result in the retrieval of similar terms, which is limited by the number of key entities from text networks considered for this comparison.

4. The top key entities from the text-based networks would not be useful labels for topics.

Additional findings only based on the Enron data are:

5. On a qualitative level, both information extraction methods return less meaningful results than with the Funding data. For example, entities consistently ranked highly with both methods include “Enron”, “energy”, and time terms. This can be because the email data are nosier, e.g. for forwarded messages, the email bodies contain time stamps and names of other people, which are reflected in both sets of results. However, this finding suggests again an agreement between the supervised and unsupervised prediction models.

6. The topics seem harder to distinct than for the Funding data, i.e. the similar gist of information seems to be suggested by multiple topics per run. This could be due to the data itself, or due to high similarity among the documents per group, which could happen for instance if multiple people have the same or similar email in their inbox.

Table 143: Topics and Key Entities, Time period 1, Group 1

	Topic										Network Metrics			
Entity	1	2	3	4	5	6	7	8	9	10	Degree Centrality	Between. Centrality	Eigenvec. Centrality	Clique Count
	0.04	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.01				
enron			x	x				x			x	x	x	x
june		x								x	x	x		x
david						x					x		x	x
energy								x			x	x		x
doug			x								x		x	
john					x							x		x
tom						x					x		x	
gas								x				x		x
steve									x		x		x	
entergy		x								x				x
hernandez		x											x	
unit					x							x		
kayne							x							x
ees								x				x		
ferc										x		x		
sent											x	x		x
miller											x		x	
please												x		x
chad													x	
mike													x	
robert											x			
watts													x	
day	x	x												
ercot	x				x									
market	x								x					
baughman	x													
don	x													
group	x													
hourly	x													
notes	x													
questions	x													
real	x													
subject		x		x										
bill		x												
coulter		x												
juan		x												
lloyd		x												
request		x												
ect			x	x					x					
hou			x	x					x					
pm			x	x										
corp			x											
enronxgate			x											

joe	x								
larry	x								
na	x								
power		x				x			
smith		x					x		
forwarded		x							
pmto		x							
tecoenergy		x							
deal			x						
enpower			x						
lcra			x						
list			x						
message			x						
mw			x						
org			x						
mdea				x	x				
reagan				x	x				
bogey				x					
chose				x					
commercial				x					
contract				x					
mann				x					
time				x					
customer					x				
data					x				
draft					x				
epmi					x				
jeff					x				
load					x				
section					x				
million						x			
risk						x			
rogers						x			
trading						x			
wholesale						x			
access							x		
bid							x		
model							x		
options							x		
tamara							x		
agreement								x	
amrn								x	
er								x	
filing								x	
Interconnect.								x	
mapp								x	
settlement								x	

Table 144: Topics and Key Entities, Time period 1, Group 2

	Topics										Network Metrics			
Entity	1	2	3	4	5	6	7	8	9	10	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01				
enron			x	x	x	x			x		x	x	x	x
energy						x					x	x	x	x
june	x		x					x			x	x		x
chris	x				x				x		x	x		x
wednesday	x										x		x	x
analyst						x					x		x	x
gas								x			x	x		x
john							x		x				x	x
firm						x							x	
transco								x				x		
gov									x			x		
sent											x		x	x
thursday											x		x	
212											x			
bob												x		
capacity												x		
doug													x	
joseph												x		
street													x	
plants														x
original	x		x		x					x				
message	x				x					x				
amto	x													
chrissent	x													
dorland	x													
items	x													
jpg	x													
pm		x								x				
add		x												
click		x												
excel		x												
exotica		x												
library		x												
meeting		x												
option		x												
options		x												
time		x												
email			x							x				
book			x											
canadian			x											
deal			x											
matt			x											
sold			x											
volume			x											
year				x			x							
corp				x					x					

subject	x						x
data	x						
days	x						
load	x						
mw	x						
pmto	x						
smith	x						
ect		x	x			x	
beer		x					
germany		x					
nyiso		x					
symptom		x					
ve		x					
earnings			x				
news			x				
ows			x				
revenue			x				
tor			x				
don				x			
lagrasta				x			
list				x			
mark				x			
model				x			
notes				x			
people				x			
trading				x			
aep					x		
bcf					x		
gri					x		
high					x		
paul					x		
rates					x		
supply					x		
mail						x	x
ca						x	
offer						x	
org						x	
fw							x
king							x
ny							x
read							x

Table 145: Topics and Key Entities, Time period 1, Group 3

Entity	1 0.10	2 0.08	3 0.06	4 0.06	5 0.06	6 0.05	7 0.04	8 0.03	9 0.02	10 0.02	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
enron	x			x			x	x	x		x	x	x	x
jeff	x						x	x			x	x	x	x
california		x					x				x	x		x
davis		x									x	x		x
energy		x									x	x		x
mara	x										x		x	
susan	x										x		x	
ferc						x						x		x
dasovich								x			x		x	
john			x											x
time			x									x		
governor					x			x						x
bill												x		x
ees											x		x	
415											x			
david													x	
gov												x		
government														x
james													x	
richard													x	
sent												x		
steffes													x	
pm	x								x					
subject	x								x					
corp	x													
fax	x													
forwarded	x													
na	x													
market		x				x			x					
power		x				x								
prices		x				x								
electricity		x												
generators		x												
state		x												
utilities		x												
alan			x											
capacity			x											
day			x											
gas			x											
message			x											
original			x											
pg			x											
sce			x											
contracts				x	x									
customers				x						x				

core	x						
dwr	x						
hertzberg	x						
noncore	x						
past	x						
rate	x						
rates	x						
group		x		x			
mail		x					x
june		x					
bankruptcy		x					
financial		x					
mou		x					
plan		x					
qfs		x					
bush			x				
cap			x				
caps			x				
commission			x				
order			x				
price			x				
call				x			
folks				x			
hoffman				x			
meeting				x			
solution				x			
week				x			
enronxgate					x		
govenar					x		
investments					x		
michael					x		
million					x		
news					x		
ca						x	
caiso						x	
confidential						x	
iso						x	
jeanne						x	
participants						x	
access							x
direct							x
edison							x
manuel							x
org							x
puc							x
tracy							x
users							x

Table 146: Topics and Key Entities, Time period 2, Group 1

	Topics										Network Metrics			
Entity	1	2	3	4	5	6	7	8	9	10	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
	0.07	0.07	0.06	0.03	0.03	0.03	0.02	0.02	0.02	0.01				
enron			x				x	x			x	x	x	x
august	x										x		x	x
september										x	x		x	x
tuesday	x										x		x	
chris	x										x			x
ercot		x	x	x								x		x
john			x			x					x	x		
time	x											x		
wednesday							x						x	
sent											x	x	x	x
monday											x		x	x
thursday											x		x	x
mike											x		x	x
friday													x	x
october												x		
november												x		
energy												x		
gas												x		
please												x		
message	x		x					x						
original	x		x					x						
pmto	x		x											
amto	x													
cowan	x													
dorland	x													
mw		x			x									
frontera		x												
hour		x												
jmf		x												
oom		x												
plan		x												
plant		x												
price		x												
resource		x												
forney			x											
joe			x											
mark			x											
subject			x											
load				x	x									
discuss				x										
list				x										
north				x										
options				x										
products				x										
trades				x										

trading	x							
zonal	x							
existing		x						
information		x						
main		x						
peak		x						
physical		x						
place		x						
power		x						
transmission		x						
scott			x	x				
call			x			x		
don			x			x		
group			x			x		
attached			x					
louise			x					
michael			x					
questions			x					
robert			x					
doc				x				
email				x				
ensr				x				
kevin				x				
received				x				
side				x				
week				x				
mail					x	x		
annulled					x			
corp					x			
duplicate					x			
intended					x			
pjm					x			
recipient					x			
communication						x		
day						x		
holiday						x		
national						x		
number						x		
work						x		
corporation							x	
cows							x	
due							x	
eps							x	
event							x	
exc							x	
major							x	
markets							x	
stocks							x	

Table 147: Topics and Key Entities, Time period 2, Group 2

	Topics										Network metrics			
Entity	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
	0.12	0.09	0.08	0.06	0.05	0.04	0.04	0.03	0.03	0.03				
enron	x	x	x		x			x			x	x	x	x
september	x		x				x				x		x	x
energy					x						x	x		x
august	x	x									x		x	
jeff	x												x	x
ferc		x										x		x
dasovich	x												x	
james		x											x	
company					x						x			
gas					x						x			
time					x							x		
bill						x								x
sent											x	x	x	x
california											x	x		x
ees											x		x	
john												x		x
monday												x		
wednesday													x	
friday													x	
dynegy												x		
electric											x			
scheduling												x		
week														x
message	x	x	x				x							
original	x	x	x				x							
pmto	x	x												
susan	x									x				
mara	x													
christi		x												
jim		x												
steffes		x												
amto			x											
herndon			x											
kevin			x											
presto			x											
risk			x											
rogers			x											
customers				x				x						
july				x										
access				x										
contracts				x										
da				x										
date				x										
decision				x										
direct				x										

dwr	x							
puc	x							
business		x						
home		x						
services		x						
tax		x						
williams		x						
assembly			x					
committee			x					
davis			x					
edison			x					
governor			x					
legislature			x					
provisions			x					
senate			x					
session			x					
draft				x		x		
mail				x			x	
arem				x				
dan				x				
douglass				x				
energyattorney				x				
mailto				x				
cpuc					x	x		
approach					x			
credit					x			
credits					x			
ctc					x			
pg					x			
px					x			
sce					x			
authority						x		
commission						x		
court						x		
federal						x		
filing						x		
issues						x		
petition						x		
rehearing						x		
donna							x	
frank							x	
group							x	
linda							x	
paul							x	
robert							x	
steve							x	
work							x	

Table 148: Topics and Key Entities, Time period 2, Group 3

	Topics										Network Metrics			
	1	2	3	4	5	6	7	8	9	10	Degree	Between.	Eigenv.	Clique
Entity	0.24	0.08	0.08	0.08	0.04	0.04	0.03	0.03	0.03	0.02	Centr.	Centr.	Centr.	Count
thursday	x										x	x	x	x
enron					x	x		x	x		x	x	x	x
august	x								x		x		x	x
september	x										x		x	x
wednesday	x										x		x	x
gas		x	x								x	x		x
energy			x									x		x
kim			x										x	
sent											x	x	x	x
tuesday											x		x	x
please												x		x
713											x			
monday													x	
friday													x	
company												x		
david												x		
houston												x		
nymex											x			
week												x		
message	x			x			x	x						
original	x			x			x							
pmto	x						x							
amto	x													
fw	x													
subject	x													
mark		x		x		x								
barry		x												
bt		x												
deal		x												
group		x												
storage		x												
tycholiz		x												
west		x												
year		x												
credit			x			x								
dwr			x											
natural			x											
power			x											
price			x											
trade			x											

trading	x							
cheryl		x						
eol		x						
greenberg		x						
jones		x						
legal		x						
tana		x						
taylor		x						
attached			x	x				
corp			x			x		
fax			x					x
america			x					
cook			x					
cordially			x					
mary			x					
north			x					
texas			x					
agreement				x				
comments				x				
dth				x				
isda				x				
nda				x				
questions				x				
frank					x		x	
allen					x			
grigsby					x			
jay					x			
mike					x			
scott					x			
tori					x			
contract						x		
heard						x		
intended						x		
mail						x		
mailto						x		
marie						x		
recipient						x		
greg							x	
kaminski							x	
predict							x	
stanford							x	
trip							x	
vince							x	

wolak									x					
ahouston										x				
sara										x				
securities										x				
shackleton										x				
shackletonenron										x				
smith										x				
street										x				
suchdev										x				
tx										x				

Table 149: Topics and Key Entities, Time period 3, Group 1

Entity	Topics										Network metrics			
	1	2	3	4	5	6	7	8	9	10	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
	0.05	0.04	0.04	0.04	0.04	0.03	0.03	0.02	0.02	0.02				
enron	x			x	x			x	x		x	x	x	x
november	x		x		x						x		x	x
october	x										x		x	x
monday				x							x	x	x	
john							x	x			x		x	x
tuesday	x										x		x	
mike			x					x			x			x
gas									x	x	x			x
wednesday	x												x	
ercot						x		x				x		
energy						x			x					x
time						x						x		
david							x					x		
sent											x	x	x	x
please											x	x		x
friday													x	x
august												x		
thursday													x	
doug												x		
smith												x		
message	x		x	x	x		x	x						
original	x		x	x	x		x	x						
pmto	x		x		x		x							
amto	x													
fw	x													
deal		x				x								
back		x												
book		x												
kam		x												

list		x									
make		x									
netco		x									
process		x									
start		x									
week		x									
chris			x								
desk			x								
dorland			x								
grigsby			x								
phillip			x								
day				x							
don				x							
group				x							
pjm				x							
pm				x							
work				x							
meeting					x		x	x			
curves					x						
data					x						
file					x						
subject					x						
power						x			x		
load						x					
market						x					
mw						x					
price						x					
sell						x					
integration							x				
kitchen							x				
louise							x				
webb							x				
ees								x			
greg								x			
mark								x			
company									x		
credit									x		
mail									x		
marketing									x		
trading									x		
transactions									x		
business										x	
daily										x	

Entity	1	2	3	4	5	6	7	8	9	10	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
keystone										x				
mexican										x				
operations										x				
socal										x				
storage										x				
units										x				
weather										x				

Table 150: Topics and Key Entities, Time period 3, Group 2

	Topics										Network Metrics			
Entity	1	2	3	4	5	6	7	8	9	10	Degree	Between.	Eigenv.	Clique
	0.08	0.05	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.01	Centr.	Centr.	Centr.	Count
california				x							x	x	x	x
enron			x				x			x		x		x
deals				x	x						x		x	
energy									x			x		x
november	x				x									x
october	x						x							x
epmi				x									x	
palo				x							x			
john								x				x		
epmi_short_term											x		x	x
southwest											x		x	x
daily											x		x	
epmi_long_term											x		x	
mwh											x		x	
northwest											x		x	
sent											x			x
monday														x
bill												x		
company												x		
dynegy														x
eol													x	
ferc												x		
gas												x		
issue												x		
jim												x		
filename	x	x												
message	x				x		x		x					
thursday	x				x									
original	x						x							
amto	x													
holden	x													

salisbury	x								
tim	x								
deal		x			x				
diana		x							
load		x							
mw		x							
pge		x							
questions		x							
scheduling		x							
system		x							
transmission		x							
power			x			x			
price			x			x			
west			x			x			
america			x						
bruce			x						
comments			x						
conference			x						
north			x						
report			x						
day				x				x	
long				x					
short				x					
sp				x					
term				x					
total				x					
group					x			x	
build					x				
cara					x				
dart					x				
fran					x				
market						x			x
cash						x			
current						x			
desk						x			
marketing						x			
prices						x			
receive						x			
fw							x		
http							x		
mailto							x		
mm							x		
pmto							x		
tag							x		
gov								x	
information								x	
intended								x	
mail								x	
provide								x	
work								x	

wscc								x						
alan									x					
caiso									x					
iso									x					
notice									x					
rto									x					
time									x					
week									x					
christian										x				
contract										x				
customer										x				
hall										x				
kind										x				
mike										x				
office										x				
year										x				
yoder										x				

Table 151: Topics and Key Entities, Time period 3, Group 3

	Topics										Network metrics			
Entity	1	2	3	4	5	6	7	8	9	10	Degree Centr.	Between. Centr.	Eigenv. Centr.	Clique Count
	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01				
enron						x			x		x	x	x	x
gas	x										x	x		x
november				x		x	x				x		x	x
david				x							x		x	x
october						x					x		x	x
monday							x				x		x	
thursday				x		x							x	
week					x							x		
team								x			x			
sent											x	x	x	x
john											x	x		x
tuesday												x	x	
company											x			x
energy												x		x
please												x		x
august												x		
friday													x	
choate													x	
new_york												x		
message	x	x		x		x	x		x					
smith	x	x												
original	x			x		x	x		x					
scott	x							x						
bateseast	x													
judy	x													

kimberly	x								
mckay	x								
vladi	x								
call		x			x				
america		x							
debra		x							
eb		x							
fax		x							
legal		x							
meeting		x							
street		x							
balance			x						
book			x						
contract			x						
cuilla			x						
curve			x						
egan			x						
leach			x						
martin			x						
point			x						
robert			x						
pmto				x		x	x		
subject				x		x	x		
december				x					
baumbach				x					
love				x					
asked					x				
called					x				
deal					x				
demand					x				
list					x				
time					x				
today					x				
told					x				
doc						x			
recipient						x			
amto							x		
fw							x		
http							x		
mail							x		
commercial								x	
desk								x	
directly								x	
logistics								x	
mike								x	
neal								x	
report								x	

shively								x			
agreement									x		
comments									x		
language									x		
master									x		
nicor									x		
party									x		
review									x		
added										x	
comwww										x	
deleted										x	
folder										x	
inbox										x	
item										x	
items										x	
offline										x	
synchronizing										x	
updated										x	

6.4.3 Application Context III: Sudan Corpus

The presented methodology is designed for situations where both, network data and text data are available. In contrast to the Funding corpus and Enron corpus, the Sudan corpus only contains text-data and non-relational meta-data, but no social network data. There are several issues with extracting the social network data from the bodies or meta-data, and then applying the presented methodology: First, if social networks distilled from text data were used, all limitations with this step (see chapters 2 and 5 for these limitations) would propagate to the grouping and text selection steps, so that any findings could be impacted by this process. Regardless, I tested the proposed methodology on the agent networks extracted from text bodies as described in section 5.2.2.2, and constructed from meta-data as explained in section 5.2.2.3. Then, I applied the Girvan-Newman grouping algorithms to these networks. The main groups contained agent nodes similar to the key players identified in 5.2.3, i.e. political leaders from the Sudan, neighboring countries, and the Western world. Since we have no texts authored by these people, as a proxy, I retrieved all texts that these people were mentioned in. This resulted in large sets, which also highly overlapped between groups, and which mentioned many other agents in addition to the key agents. For the given reasons and based on the described pre-tests, I decided to not further test the proposed methodology on the Sudan corpus. The conclusion for this application context is that the proposed methodology is not appropriate for corpora on which no explicit or meaningful network data is given.

6.5 Conclusions

In this chapter, a computational and interdisciplinary methodology for jointly considering text data and network data was developed, operationalized, and tested on two real-world datasets. The resulting methodology facilitates the enhancement of social network data with content nodes, and fixes the main limitation with this approach, namely the arbitrary identification of content nodes, and which agents these nodes are linked to. The proposed methodology scales up to large corpora. At the same, the methodology allows for gaining an in-depth understanding of the content that groups of structurally coherent agents are exposed to directly or within a few steps in their social network. However, further work would be needed to fully automate this process. The next section suggests some strategies for that.

The methods review in this chapter has led to the following conclusions: first, extracting content nodes from groups of *structurally equivalent* agents is an appropriate strategy for enabling the *comparison* of the content that these agents produce, perceive or disseminate. Also, these equivalence classes can represent a variety of social roles and positions that network members can occupy. These roles include classic network power roles that are defined over node centrality metrics, other structurally defined roles, such as formal and informal leaders, and also roles defined over behavioral signatures, such as homophily. Second, extracting content nodes from groups of *structurally coherent* agents is an appropriate strategy for enabling the *enhancement* of social network data with content nodes. Since this enhancement process was the main goal with this chapter, the second strategy was selected for further work herein.

Operationalizing the proposed methodology and applying it to two datasets has suggested the following findings: first, even though the overlap between key entities from meta-data knowledge networks and members of high-scoring topics is minimal on the string identify level, the entities that score highest with respect to node centrality metrics seemed to be great fits for labels for topics. In future work, the appropriateness of this strategy for automatically finding labels for topics can be further explored. This strategy could supplement or replace the approach of using the most likely term per topic as the topic label.

Second, most of the key entities from the text-based knowledge networks also occur as topic members. This was observed for generic terms from the tested domains and datasets as well as for domain-specific terms. This relationship between members of topics and key entities from text-based networks is asymmetric, i.e. topic modeling outputs contain terms that do not occur in key entities from the text-based networks. This is mainly due to the number of key entities retrieved (top ten) and their high overlap across network metrics (total pool of entities smaller than with topic modeling). The analysis of the terms found in highly ranked topics but not among

the key entities revealed that many of these terms were removed from the thesaurus generated by using the entity extractor built with supervised learning in chapter 3, as they were noisy or overly generic. This finding suggests that the most salient entities found with supervised (CRF) versus unsupervised (topic modeling) learning applied to the same new inference leads to the retrieval of:

1. Similar terms through different methods term ranking methods, i.e. grouping words into sets of entities generated from the same topics (topic modeling) versus grouping nodes into sets of structurally entities (key entity analysis).
2. The same noise terms. This implies two more findings:
   - Topic modeling can benefit from the same cleaning techniques that were used for the output of the entity extractor. Thus, the same delete lists and entity merger lists can be used for both outputs.
   - Applying the same cleaning techniques consistently to both output sets might further increase the similarity between the results from both methods. This assumption can be tested in future work.

The latter finding also explains why in contrast to the top key nodes from the meta-data networks, the key entities from the text-based networks would not server as useful labels for topics.

Third, even though the comparison between the key entities from the reference networks (meta-data and text-based) was not the focus of this study, a side-product of this chapter was finding out that for either network type, the key entities are highly similar across the considered network metrics. This finding further complements the outcome of the previous chapter by showing that key entities differ across network types, but are highly within networks constructed from the same data with either one method.

In summary, besides the proposition and testing of a methodological improvement, a second contribution with this chapter was the comparison of the results from topic modeling; an efficient and unsupervised information extraction technique, to the outcome of alternative methods, including supervised entity extraction. Clearly, such comparisons cannot replace rigorous validations of topic modeling by comparing the results against ground truth data. However, such ground truth data might be expensive to collect: for example, with respect to the Funding corpus, we have some expertise in a few research domains, but are not qualified to evaluate topics from proposals from the last 18 years and a wide range of areas. Finding subject matter expert who are qualified to make these judgments is likely to be expensive. Therefore, contrasting the outcome of topic modeling against alternative methods helps to understand the results of topic modeling

in the wider context of information extraction methods. The comparisons in this chapter have led to the following conclusions: first, identifying content nodes from text-based knowledge networks by performing key player analysis retrieves only a small portion of entities that would not be found with topic modeling. Second, the key entities from meta-data knowledge networks might not only serve as good labels for topics, but might also be suitable proxies for some of the topics found with topic modeling. The validity of these assumptions needs to be tested in future work.

6.6 Limitations and Future Work

This chapter as well as the other previous ones in this thesis have shown that applying clearly defined information extraction methods involves a plethora of decisions to make, which impact the analysis results. In this chapter, nodes had to be grouped into partitions, and a large part of the methods and operationalization section had to be devoted to this point. However, grouping is a science and art of its own, and not the focus of this chapter. Also, the grouping algorithm used herein as well the other common grouping techniques are defined for symmetric data. Since both of the social networks used in this chapter are not symmetric, they had to be symmetrized prior to grouping. The same limitation, i.e. adjusting the actual characteristics of the data to the properties required for a computational routine, also applies to most of the network metrics used in this thesis; with many of them being defined for squared, undirected, and binary matrices (see Table 153 for this information). Most software tools automatically convert these data properties such that they are compatible with the requirement for a metric, including ORA, but the potential recuperations of this procedure on analysis results still need to be considered.

Another limitation that has also been observed in a prior chapter (4) is the incompatibility of tools: the original Funding data are represented in the UTF8 encoding. Therefore, I used the same encoding for the relational database in which I managed the data. However, ORA uses ASCII encoding, which converted non-ASCII letters into other symbols. Importing networks into ORA caused changes in the spelling of some agent nodes, and these altered names would not match the database anymore when retrieving the texts per person. However, these changes are not always obvious, and adjusting them back to the original stepping would have been very time consuming.

In future work, the following methodological extensions to the procedure presented in this chapter seem relevant:

First, the identification of content nodes per group was done on a case-by-case basis for the largest groups per time period. This process can be further speeded up by performing the following steps automatically: pick the first N nodes from the first N topics, label them with a

generic or specific theme label per topic, e.g. the strongest term or key entity from meta-data network, and fuse the knowledge network with the social network. While technically, this procedure can be added to ORA by re-using existing routines, the validity of this process needs to be further tested on more datasets.

Second, the identification of content nodes can be performed not only on the level of positions, roles or groups of agents, but also on the text corpus level. This extension could serve two purposes: first, comparing the outcome of grouping agent nodes by employing grouping algorithms from social network analysis against grouping agents based on shared content, i.e. topics that multiple people are involved in. McCallum et al. (2007) have shown how clustering agent nodes based on topic modeling can outperform clustering of agents based on partitioning social network data via grouping algorithms. However, in that work, dyads between email senders and receivers were identified. This idea can be extended to larger groups of people. Second, the social network could be enhanced with links between agents who are associated with the same content, but have not co-authored a document. This step serves three purposes: verify existing links between agents, identify missing links between agents, and suggest additional ties between agents as well as knowledge nodes. This extra step would also allow for adding the impact of language use on network structure into the network data, but further studies are needed first to test for the validity of this approach.

Third, based on the conclusions from this chapter, it also seems worthwhile to test the appropriateness of using key entities from meta-data networks as labels for topics in a more rigorous fashion and on additional datasets. This type of comparison can also serve another purpose: when topic modeling is performed on a per document basis, the identified topics can be manually labeled, and the resulting labels compared against the keywords that the authors had selected per document. This comparison helps to understand the agreement or mismatch between top-down categorizations of documents, e.g. via pre-defined or self-defined keywords, versus bottom-up classifications of documents that emerge from the content of the text data.

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Appendix

Table 152: Full name and LDC ID number for datasets

Short name	Full name	LDC ID number
MUC 6	Message Understanding Conference (MUC) 6	LDC2003T13
MUC 7	Message Understanding Conference (MUC) 7	LDC2001T02
ACE 2	Automated Content Extraction (ACE)-2 Version 1.0	LDC2003T11
TIDES 2003	TIDES Extraction (ACE) 2003 Multilingual Training Data	LDC2004T09
ACE 2004	ACE 2004 Multilingual Training Corpus	LDC2005T09
ACE 2005	ACE 2005 Multilingual Training Corpus	LDC2006T06
reACE	Datasets for Generic Relation Extraction (reACE)	LDC2011T08
BBN	BBN Pronoun Coreference and Entity Type Corpus	LDC2005T33
SemEval 2010-8	SemEval-2010 Task 8: Multi-Way Classification of Semantic Relations Between Pairs of Nominals	n.a.
Onto Notes 4	OntoNotes Release 4.0	LDC2011T03
SemEval 2010-1	SemEval-2010 Task 1: OntoNotes: Coreference resolution in multiple languages.	LDC2011T01
NYT AC	The New York Times Annotated Corpus	LDC2008T19
CoNLL 2003	CoNLL-2003 task: Language-Independent Named Entity Recognition	n.a.

Table 153: Network Analysis Measures used in thesis*

Metric	Definition	Range of output values**	Input converted to	Level of analysis	Reference
Average Distance	The average shortest path length between nodes, excluding infinite distances.	0, N	square, binary	Graph	(Wasserman & Faust, 1994)
Average Speed	The average inverse geodesic distance between all node pairs. The highest score is achieved for a clique, and the lowest for all isolates	0,1	square, binary	Graph	(K.M. Carley, 2002b)
Betweenness Centrality	Per node *i*, across all node pairs that have a shortest path containing *i*, the percentage that pass through *i*.	0,1	square, binary	Node	(Freeman, 1979)
Betweenness Centralization	Network centralization based on the betweenness score for each node in a square network.	0,1	square, binary	Graph	(Freeman, 1979)
Clique Count	The number of distinct cliques to which each node in a network belongs. A clique is a maximal complete subgraph of three or more nodes.	0, N	square, symmetric	Node	(Wasserman & Faust, 1994)

Component Count Strong	The number of strongly connected components in a directed network. This is computed directly on G, whether or not G is directed.	0,N	square, binary	Graph	(Wasserman & Faust, 1994)
Component Count Weak	The number of weakly connected components in a directed network. Such components are called "weak" because the graph G is undirected.	0,N	square, binary, symmetric	Graph	(Wasserman & Faust, 1994)
Degree Centrality	The normalized in-degree plus out-degree of a node. I.e. the size of the immediate ego-network of a node.	0,1	square	Node	(Wasserman & Faust, 1994)
Degree Centralization	A centralization of a square network based on total degree centrality of each node.	0,1	square, symmetric	Graph	(Freeman, 1979)
Connectedness	Measures the degree to which a square network's underlying (undirected) network is connected.	0,1	square, symmetric	Graph	(D. Krackhardt, 1994)
Density	The ratio of the number of edges versus the maximum possible edges for a network.	0,1	N, L	Graph	(Wasserman & Faust, 1994)
Diffusion	The degree to which something could be easily diffused (spread) throughout the network. This is based on the distance between nodes. A large diffusion value means that nodes are close to each other, and a smaller diffusion value means that nodes are farther apart.	0,1	square, binary	Graph	(K.M. Carley, 2002b)
Efficiency	The degree to which each component in a network contains the minimum edges possible to keep it connected.	0,1	square, binary, symmetric	Graph	(D. Krackhardt, 1994)
Eigenvector Centrality	The centrality of a node based on its degree and the degrees of its neighbors.	0,1	square, symmetric	Node	(Bonacich, 1987)
Eigenvector Centrality	Calculates the eigenvector of the largest positive eigenvalue of the adjacency matrix representation of a square network.	0,1	square, symmetric	Graph	(Bonacich, 1987)
Fragmentation	The proportion of nodes in a network that are disconnected.	0,1	square, binary, symmetric	Graph	(Borgatti, 2003)

Global Efficiency	Global Efficiency is the normalized sum of the inverse geodesic distances between all node pairs.	0,1	square, binary, symmetric	Graph	(Latora & Marchiori, 2001)
Hierarchy	The degree to which a network exhibits a pure hierarchical structure.	0,1	square, binary	Graph	(D. Krackhardt, 1994)
Inverse Closeness Centralization	The average closeness of a node to the other nodes in a network. Inverse Closeness is the sum of the inverse distances between a node and all other nodes.	0,1	square, binary	Graph	(Wasserman & Faust, 1994)
Network Levels	The Network Level of a square network is the maximum Node Level of its nodes. This measure is also called diameter.	0, |N|-1	square, binary	Graph	(Kathleen M. Carley, et al., 2011)
Clustering Coefficient	Measures the degree of clustering in a network by averaging the clustering coefficient of each node. The clustering coefficient of a node is the density of its ego network - the sub graph induced by its immediate neighbors.	0,1	square, binary	Graph	(D.J. Watts & Strogatz, 1998)
Transitivity	The percentage of edge pairs (i,j), (j,k) in the network such that (i,k) is also an edge in the network.	0,1	square, binary	Graph	(Kathleen M. Carley, et al., 2011)
Upper boundedness	The degree to which pairs of agents have a common ancestor.	0,1	square, binary	Graph	(D. Krackhardt, 1994)

* For more details on these metrics see (Kathleen M. Carley, et al., 2011). Definitions are partially preprinted from that source.

** Definitions: N = number of nodes, L = number of links

Table 154: Error Analysis, Class Model 3, absolute values

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Table 155: Error Analysis, Class Model 4, absolute values

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	Prediction																																
Ground Truth	agent na	attribute age	attribute numerical	event na	event war	knowledge art	knowledge language	knowledge law	location city	location country	location facility	location other	location state-prov	none	org. corporate	org. edu	org. gov	org. other	org. political	org. religious	org-att nationality	org-att other	org-att political	org-att religious	resource animal	resource disease	resource money	resource plant	resource product	resource substance	task game	time na	Sum
agent na	45,418		10	17		166			318	8	29	15	24	2,548	791	12	35	49	2	1	5		20		5		5		21	1	1	27	49,528
attribute age		764	160			1					1			111													1		4			52	1,094
attribute numerical	8	129	28,995			11					6	1		1,439	23			1									58		6			314	30,991
event na	18		1	426		35			8	3	4	5		68	14		3		1										4	2		37	629
event war				2	110					3				2	3						2												122
knowledge art	268		11	9		1,040		4	65	6	12	10	5	479	167	9	18	23		6	8			3	4	1			11	4		38	2,201
knowledge language	12					4	43	2				2		13							10												86
knowledge law	7		23	3	2	15		695	5	3				87	37		4	11											5			10	907
location city	435		1			58			6,667	28	27	75	17	152	335	14	20	39	4	2	3						2		1			9	7,889
location country	32		1			7		1	21	6,329	1	46	13	120	49	1	64	11				4					1						6,701
location facility	88	2	24	2		66		3	71	3	2,182	14	12	763	151	17	28	24	2		3						2		3	3		10	3,473
location other	86		8	5	1	28			101	52	19	1,475	16	147	110	2	8	12			5				2					1		5	2,083
location state-prov	51					5			102	17	1	9	2,838	430	49	2	14	4	2													6	3,530
none	1,012	52	1,489	20		517	2	40	144	25	353	60	67	889,453	2,522	28	246	207	5	7	26	3	5	2	31	34	541	12	267	255	25	3,118	900,568
org. corporate	2,161		69	3		254		12	384	134	94	182	125	4,486	54,724	37	325	252	1	1	30		1	4	1		6		49	2		45	63,382
org. edu	33					18			24	1	3	3	7	96	52	971	21	14		2									1				1,246
org. gov	112		2	5		33		10	20	23	9	31	6	375	506	3	9,691	75	3		7		1				2		8	1		2	10,925
org. other	164		7			75		8	107	10	18	48	8	478	512	16	95	3,077	3	20	5	3	1		4		3		1	1		5	4,669
org. political	37					2								94	60	2	3	65	504			1	28									2	798
org. religious	13					2			2		3			30	13	1	2	4	1	77				2					2				152
org-att nationality	88		1			7	1		13	4		6		42	32		10	4	3		3,300	7	6	2					6			6	3,538
org-att other	15						1		8	2		1		19	4			4			8	33										1	96
org-att political	32											1		11	4		5		26		2		601										682
org-att religious	6								1					6	10				1	1	7		1	56	4							1	94
resource animal	26					12			1					202	3										168				1				413
resource disease	10								1					170	1											194				1		1	378
resource money	2	2	139						1	2				607	2			3			3						30,905					20	31,686
resource plant	9								2		28			61	1													96		1			198
resource product	190	5	89	9		138		5	36	1	2	11	4	505	225	8	5	14			15				2	5	7		1,334	8		45	2,663
resource substance	42	3	31	1		2			12					931	48	1		3			3			2	2	1	1	2	20	1,697		6	2,808
task game	10													59	5																24		98
time na	20	17	532	8		17		4	3	1		3		2,165	13						9						18		2	1		39,439	42,252
Sum	50,405	974	31,593	510	113	2,513	47	784	8,117	6,655	2,792	1,998	3,142	906,149	60,466	1,124	10,597	3,896	558	117	3,451	51	664	71	223	235	31,552	110	1,746	1,978	50	43,199	1,175,880

Ground Truth \ Predictions	agent_generic_na	agent_specific_na	attribute_na_age	attribute_na_numerical	event_specific_na	event_specific_war	knowledge_specific_art	knowledge_specific_language	knowledge_specific_law	location_generic_city	location_generic_country	location_generic_facility	location_generic_other	location_generic_state-prov	location_specific_city	location_specific_country	location_specific_facility	location_specific_other	location_specific_state-prov	none	org_generic_corporate	org_generic_edu	org_generic_gov	org_generic_other	org_generic_political	org_generic_religious	org_specific_corporate	org_specific_edu	org_specific_gov	org_specific_other	org_specific_political	org_specific_religious	orgatt_specific_nationality	orgatt_specific_other	orgatt_specific_political	orgatt_specific_religious	resource_generic_product	resource_na_animal	resource_na_disease	resource_na_money	resource_na_plant	resource_na_substance	resource_specific_product	task_na_game	time_na_na	Sum
agent_generic_na	25,269	57	1	5	5		32			1	4	4		1	10		2	2	9	2,224	299		10	38	2	1	41	5	16	17	1	1	2		2		9	6	1			1	4	1	7	28,013
agent_specific_na	31	16,840		8	18		151		6						360	6	30	12	34	442	4						591	14	8	17		1	1		2			3	9	1		1	47		30	21,515
attribute_na_age			782	178													2			110							1	1															6		24	1,094
attribute_na_numerical	1	4	124	28,960	3		6		1								7	2		1,446	1						20			2										72			9		111	30,991
event_specific_na		15		1	434		28		2						7	1	9	3		63							19		5		1											1	4		35	629
event_specific_war					2	113										3				2													2													122
knowledge_specific_art	30	179		13	4		1,068	2	7						37	3	33	10	1	476	1			1			169	4	11	27		7	2	2		2	1	4	3	1		4	26		33	2,201
knowledge_specific_language		8		1			3	40									1	2		15							1						12													86
knowledge_specific_law	3	7	1	29	3	1	13		708						4	1				81							18		8	14													8		3	907
location_generic_city	4									293		7	2		3			1		63	3		1																							377
location_generic_country	12									3	865	2		8						82	12		3	2			2																			993
location_generic_facility	2	2					1			1	1	1,760			4		3			738	33		3	3			3	1	1		1							1		1		3			4	2,598
location_generic_other	2		2							4		4	13					1		25	1			17																						69
location_generic_state-prov	1									2	3	1		210		1			2	172							1	1																	1	397
location_specific_city	5	303		1	1		46		2	3					6,613	27	11	60	5	136							213	12	3	34	4	3	1							1			5		3	7,512
location_specific_country	1	16		1		1	4		1					1	33	5,398		11	13	20	1						29		36	5				2				1		2						5,708
location_specific_facility	3	72	1	20	2		32		3			7			22	5	412	14	10	50			1				99	11	14	10		5		2						2			10		7	880
location_specific_other	5	67	1	6			24		1		1	1	1		53	46	3	1,447	10	127							151		10	17		2	4						1			1	3		4	2,014
location_specific_state-prov	3	33		2			2							2	119	7	1	11	2,572	193							49	1	8	3									1						3	3,133
none	585	242	62	1,461	28		515	2	40	34	9	650	2	55	101	19	33	54	31	888,849	687	11	33	65	2	5	1,971	45	160	133	9	8	30	6	3	4	196	37	40	545	11	280	58	28	3,113	900,568
org_generic_corporate	410	3	1	14			3					30					1	2		928	13,331	2	148	108	2	1	33	3	2				1				6			1	1	1			2	15,303
org_generic_edu	6										2	1	1							28	12	178	2	2	1		3	4		2																248
org_generic_gov	57									1	2	3		6	1					109	259		2,021	24	1		1		5								1									2,521
org_generic_other	72		1				4				2	20	4			1				202	157		21	827		2		1	4	13							3			2					2	1,343
org_generic_political	11										1									20	18	1	4	27	78		1																			161
org_generic_religious	1											1								16	2	2	2	1		24						1					1									51
org_specific_corporate	87	1,613	1	33	2		201		21		1			1	412	53	33	176	41	3,104	22					2	41,968	44	390	140	3	8	17	2			1	1		5		2	74		41	48,077
org_specific_edu	5	18		1			9								30	2	7	2	5	52							42	779	13	34	9															1,001
org_specific_gov	22	91		9	9		25		9					2	13	16	33	29	4	265	4		3	1	9		247	4	7,620	47	2	2	4		1		1			1		1	6		3	8,404
org_specific_other	36	39		6	1		84		12						43	5	14	86	10	249	4		1	34	1		103	17	88	2,231		12	3	4		2		2		1			2		3	3,320
org_specific_political	6	13					2								4					81				11			16	6	4	31	419				29								2		1	647
org_specific_religious	3	6					3								4		3			9			1				4		3	1		49				3							2			101
orgatt_specific_nationality	27	22		5			2	9			1				13	1	1	9		62							90	1	2	4	9		3,319	6	4	2							5		3	3,596
orgatt_specific_other	2	4			1		2	1							7	1		1		25							5	1		4			3	39									1			96
orgatt_specific_political	17	2													1			1		18							6		2		21		3		617											682
orgatt_specific_religious	13	2																		8										2		1	3		2	56		4					2			94
resource_generic_product	2	1	2				3					2					1			844	25						5	1	2								1,001		2			1	2		4	1,897
resource_na_animal	5	14					17								1					199	2			1			5											167	1				1			413
resource_na_disease	1	8													1					179							2												182			1				376
resource_na_money	1	2	2	187											2	4			1	330	4			1			1						2							30,938			2		13	31,688
resource_na_plant	1	1		2			1					23								67										2											96					193
resource_na_substance	12	13	2	34			4								3					914		1					31						1					5	2		2	1,742	31		3	2,808
resource_specific_product	17	111	5	68	4		153		5						44		35	7	4	159							197	3	6	13	9		2						9	7		7	354		43	1,266
task_na_game		1					2													60							3														1			29		98
time_na_na	5	14	21	468	7	1	81		8		2	2			2		2	1		2,138				1			18		1	1			10							20		1	8	1	39,434	42,252
Sum	26,825	22,498	960	31,540	507	116	2,490	51	816	342	896	2,155	28	286	8,057	5,772	779	1,897	2,612	906,133	15,272	195	2,253	1,161	88	38	45,589	954	8,226	2,881	466	95	1,419	59	660	69	1,214	231	251	31,620	111	2,048	668	59	43,213	1,175,880

I. Guideline for adding content nodes to existing networks in ORA

1. Generate a network per group (analysis -> generate reports -> characterize groups and networks -> locate sub-groups). These networks are a default output from grouping nodes.
2. Check if the node class "knowledge" already exists. If not, create one (add new node class -> knowledge).
3. In the node class editor, enter the ID and title for each node, .e.g. "transportation". The same token will serve as ID and title. This information can also be imported with the import wizard from a .csv file, which contains one header row ("knowledge"), and the content of each knowledge node in a separate line.
4. Check if a knowledge x group network already exists. If not, create one (add blank network -> source node class: groups, target node class: knowledge).
5. In the "Editor" for the knowledge x group network, connect knowledge nodes to groups by checking the respective boxes.